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Three Essays on Reporting and Disclosure

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Abstract

This Thesis presents three studies on financial reporting and disclosure. In chapter one we study if quarterly earnings guidance causes managerial short-termism, in the form of real earnings management. Next, in chapter two we study the links between conditional conservatism and voluntary disclosure of management private information. Finally, in chapter three we study how firms respond to lower levels of disclosure from rivals.

Esta Tesis presenta tres estudios sobre la información financiera suministrada en los estados contables y la revelación voluntaria de información de la firma. En el primer capítulo se estudia el efecto de emitir previsiones trimestrales de ganancias en la predisposición de los gerentes a concenrtarse excesivamente en las ganacias de corto plazo, induciendo potencialmente manipulación en las operaciones de la firma. En el segundo capítulo se estudia la relación entre el cosnervadurismo condicional y la decisión de los gerentes de revelar información privada de la firma voluntariamente. Finalmente, el tercer capítulo estudia la respuesta de las firmas cuando sus competidores emiten menos información al mercado.

Introduction

Accounting information (i.e. mandatory financial reports) is only a subset of the information available to investors, and firms usually have more information than what is disclosed in its financial reports. Most likely, this information is 'good news' due to the properties embedded into accounting frameworks (i.e. stringent verification requirement for the recognition of good news). One way for managers to convey this 'good news' to the market is trough voluntary disclosure (e.g earnings forecasts), but managers might act strategically using voluntary disclosure to serve their own purposes (e.g. maximize compensation). Consequently, 'non-accounting' information signals might be incrementally beneficial to investors depending on its properties and the properties of the accounting information, leading potentially to different impacts on firms characteristics (e.g. cost of capital, stock performance, firm value). On the other hand, managerial incentives underlying voluntary disclosure might lead to different consequences (e.g. managerial myopia) casting doubt on the benefits of voluntary disclosure (i.e. short-term forecasts), and whether is a good practice or not. Finally, information released by one firm might have consequences on other firms stock price if they face the same economic conditions or have similar earnings determinants (i.e. information-transfers). Firms might voluntary disclose information to intervene in the information-transfer process when disclosure by its peers has negative consequences. However, the decision to voluntary disclose their private information will depend on a rational assessment of the trade-offs between the costs (e.g. litigation risks, disclosure costs, proprietary costs) and benefits (e.g. increasing stock prices) associated with the disclosure.

I study the aforementioned issues in this Doctoral Thesis. In chapter one, **The Effect of Quarterly Earnings Guidance on Real Earnings Management** (with Beatriz García Osma and Encarna Guillamón Saorín), we study the relationship between short-term earnings guidance and real earnings management. Some regulators, practitioners and investors claim for the discontinuation of short-term guidance arguing that this practice fosters short-termism. However, empirical research on the matter finds mixed evidence. We argue that this mixed evidence found by previous papers is driven by two factors. First, previous literature studying the relation between short-term guidance and short-termism ignores the underlying motives for issuing guidance (i.e. treat all guidance as equal). Second, previous papers fail to control adequately for endogeneity. These two factors might reduce the power of the tests and introduce a correlated omitted-variables problem making the results difficult to interpret. To mitigate these concerns we exploit exogenous decreases in analyst coverage due to brokerage closure as a shock to firms information environment. Brokerage decisions to close research operations are related with industry trends, regulatory changes, and strategic reasons not related with fundamentals of the companies they cover. Therefore, coverage terminations related with brokerage closure are likely to be exogenous to firms fundamentals. We use this setting to identify instances in which guidance is made in response to an exogenous shock to firms' information environment. In this way we separate informative from strategic earnings guidance and test if quarterly earnings guidance causes managerial short-termism, in the form of real earnings management. Our results indicate that managers issuing informative guidance, engage in less real earnings manipulations relative to managers issuing non-informative or strategic guidance. We interpret this result as informative guidance alleviating short-termism. This is consistent with the expectation alignment hypothesis of Ajinkya and Gift (1984) where guidance helps to reduce information asymmetries and reduce the need of managers to engage in real earnings management to meet earnings targets. In addition, our results are also consistent with non-informative guidance increasing market pressures to meet earnings targets and leading to higher levels of real earnings management. These results reconcile mixed evidence found by previous literature (i.e. strategic guidance fosters short-termism while informative guidance alleviates short-termism) and suggest that whilst some guidance may indeed be associated with suboptimal managerial decision-making, not all guidance has this negative consequence.

In chapter two, **Conditional Conservatism and Management Earnings Forecasts** (with Beatriz García Osma). We study whether conditional conservatism allows 'soft' sources of information to flourish. Conservatism may attain this benefit because 1) it acts as a governance mechanism that reduces managerial incentives and ability to manipulate accounting earnings, and 2) it provides a benchmark for current performance that enables other sources of information to produce credible information. We show that more conditionally conservative firms issue more (less) good (bad) news earnings forecasts, and that good news forecasts are associated with greater market reactions (i.e analyst revisions and cumulative abnormal returns) for conditionally conservative firms, signaling greater credibility of disclosure. This is consistent with conditional conservatism acting as a mechanism that lends credibility *ex-ante* to voluntary disclosure by providing a "hard" reporting benchmark that allows outsiders to better evaluate the credibility of management forecasts. The results are robust to considering an exogenous shock to conditional conservatism (i.e. implementation of SFAS

142). We also verify that the association between conditional conservatism and good news earnings forecasts is moderated as theory would predict. We find a stronger (weaker) association when the firms face high (low) information asymmetries, and when managers have less (more) career concerns. Additionally, we show that the association of conditional conservatism and market reactions to good news earnings forecasts is stronger during "crisis of trust" periods, when signals of credibility are more valuable. We contribute to the conservatism literature by presenting empirical evidence on the benefits of conditional conservatism for firms' information environment. We show that conditional conservatism is a mechanism by which managers can commit to truthfully disclose earnings forecasts. In addition, we contribute to the debate on whether financial reporting and voluntary disclosure are complements or substitutes, by showing that conditional conservatism acts as a complement for timely voluntary disclosure of good news and a substitute for timely disclosure of losses. By providing a "hard" reporting benchmark, conditional conservatism enhances the information value of good news earnings forecasts.

In chapter three, **Firms Reaction to Peers Non-Disclosure** (with Beatriz García Osma), we study how firms respond to lower levels of disclosure from rivals. Prior literature suggests that managers might voluntarily disclose private information to counteract negative information transfers from rivals disclosure. We exploit the staggered adoption of the inevitable disclosure doctrine (IDD) by U.S. state courts, as an exogenous shock to the information environment of peer firms in non-IDD states. We find that peer firms in non-IDD states are less likely to conceal customer identity after IDD adoption. Our results are stronger when industry leaders are headquartered in IDD adopting states, and for firms in industries facing strategic complements interactions and low product market flexibility.

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Chapter 1

The Effect of Quarterly Earnings Management on Real Earnings Managements

1.1 Introduction

We study if firms that issue quarterly earnings guidance engage in greater real earnings management. Providing short-term forward-looking earnings forecasts, commonly referred to as "earnings guidance," is a widespread practice among US firms. However, practitioners and regulators have increasingly opposed such guidance, raising concerns that short-term earnings guidance may lead to: (1) an inefficient consumption of managerial attention, as managers dedicate time to produce and communicate their forecasts to the market instead of focusing on the firm's long-term growth objectives; (2) increased earnings management to meet those forecasts; and (3) an increased likelihood of attracting investors with a short-term focus. These concerns have led to calls for the discontinuation of guidance to avoid short-termism and myopic behavior.[1]

Anecdotal evidence suggests that several companies have followed this recommendation and announced their decision to stop providing guidance. For example, The Coca-Cola Company announced on December 13th 2002 the decision to stop providing earnings guidance in the future. Gary Fayard, CFO of the company at that time, stated that "*it will allow the company to continue to focus on*

[1] As representative examples, the consulting firm McKinsey suggests that "companies that currently provide quarterly earnings guidance should shift their focus away from short term performance and toward the drivers of long-term company health" (Hsieh et al., 2006), the CFA Institute panel of experts recommends to "end the practice of providing quarterly earnings guidance"(Krehmeyer et al., 2006), and the U.S. Chamber of Commerce encourages public companies to "eliminate the practice of providing quarterly earnings guidance" (U.S. Chamber of Commerce, 2007)

long-term growth objectives, which is good for our shareholders and not managed in the short-term quarter-to-quarter" (2002-Q3 Earnings Conference Call).

Against this backdrop, a natural question that arises is whether short-term guidance generates incentives for real earnings management. Real earnings management refers to operating, investing and financing decisions taken with the ultimate objective of reporting earnings numbers that misrepresent true performance (Schipper, 1989; Roychowdhury, 2006). If earnings guidance creates pressures to take sub-optimal decisions that ensure reported earnings meet management earnings forecasts, it logically follows that guidance may create incentives for real earnings management. In line with this view, the survey evidence in Graham et al. (2005) suggest that managers do engage in real earnings management to meet their own earnings forecasts. However, guidance is not without benefits,[2] and prior literature offers mixed views and conflicting evidence on the effects of guidance on real business decisions. Focusing on mandatory reporting, Gigler et al. (2014) analytically demonstrate that frequent reporting of results affects firms' project selection strategies. Specifically, they show that the price pressure created by high reporting frequency induces managerial myopia. Looking more directly at voluntary reporting of results, Cheng et al. (2007a) show that quarterly earnings guidance frequency is associated with research and development (R&D) underinvestment, consistent with the arguments in Gigler et al. (2014). In contrast to these results, Houston et al. (2010) find no evidence of firms having greater investment in capital expenditure and R&D after stopping guidance, relative to firms that continue issuing guidance.

We expect that this lack of conclusive findings may be explained by two factors. First, prior studies usually consider all earnings guidance as homogeneous. This ignores managerial motivations. Kim and Park (2012) argue that guidance may be associated with either a) expectation management (i.e., issued with the purpose of meeting or beating market expectations), or b) communication incentives (i.e., issued to convey reliable information to the market), highlighting the importance of considering the particular managerial incentives underlying the guidance issued. Second, given that the decision to issue guidance is voluntary, endogeneity problems can arise as a consequence of self-selection or omitted-variable bias.[3]

In this paper, we revisit the question of whether short-term guidance creates incentives for sub-optimal decision making and contribute to prior research by focusing on its effects on real earnings management. In doing so, we build on prior work to address the two identified concerns as follows. First, we acknowledge the role of managerial incentives and identify guidance as either informative or

[2]For example, managerial forecasting aids to reduce information asymmetries (Healy and Palepu, 2001).

[3]Treating all guidance as equal and not controlling adequately for endogeneity may lead to power test reductions and correlated omitted-variables problems (Li et al., 2011a, 2012, 2016)

strategic.[4] We argue that only strategic guidance creates managerial pressure to meet self-imposed targets, leading to real earnings management. Guidance is *strategic* when managers attempt to manipulate expectations opportunistically and with no informative motive, for example, to "hype" stock prices around equity offerings (Lang and Lundholm, 2000), or to profitable trade in their firm's shares (Noe, 1999; Cheng et al., 2007a). In contrast, guidance is *informative* when it reduces information asymmetry (Ajinkya and Gift, 1984; Dutta and Gigler, 2002).

Second, we identify as informative those management earnings forecasts issued in response to an exogenous decrease in analyst coverage arising from brokerage house downsize (Yu, 2008; Anantharaman and Zhang, 2011). This design alleviates endogeneity concerns and allows us to draw causal inferences. Analyst coverage is valuable for managers because it drives investor attention and liquidity, therefore managers have incentives to issue guidance to attract or retain coverage (Rana, 2008). Prior literature finds evidence that exogenous decreases in analyst coverage deteriorate firms' information environment and that managers respond by increasing voluntary disclosure (Kelly and Ljungqvist, 2007; Hong and Kacperczyk, 2010; Balakrishnan et al., 2014).

By focusing on real earnings management we can account for a number of managerial sub-optimal operating and investment decisions. Existing research on the association between guidance and short-termism focuses mainly on R&D expenses (Cheng et al., 2007a; Houston et al., 2010) or accruals earnings management (Call et al., 2014). In contrast, real earnings management proxies capture aggregated managerial short-termism. This permits providing novel evidence on the strategies followed by managers who issue short-term guidance. Indeed, real activities manipulations better captures managerial short-termism since it has direct effects on firms' future cash flows, which potentially conveys higher long-term costs on the company (Khurana et al., 2017).

We test our prediction that strategic (informative) guidance leads to greater (lower) real earnings management on a large sample of US publicly listed firms over the period 2003-2013. We exclude all firms that might be subject to specific institutional and regulatory constraints. We follow Roychowdhury (2006) and Zang (2012) to measure real earnings management and use the I/B/E/S Guidance database to identify firms issuing quarterly earnings guidance. We include all guidance made between 0 and 90 days before the quarter-end. Doing this ensures that we focus in short-term quarterly forecasts and avoid including stale forecasts and earnings pre-announcements in the sample. As previously described, we follow a modified Yu (2008) procedure as in Anantharaman and Zhang (2011) to identify informative guidance.

[4] Another possible incentive to issue guidance is to comply with insider trading rules, SEC rule 10b-5 prohibit managers from trading using material private information (Li et al., 2011a).

Our tests provide the following key findings. We find that strategic guidance leads to greater real earnings management. In contrast, we find evidence that informative guidance is negatively associated with real earnings management. We interpret these results as indicating that strategic guidance increases short-termism, i.e., with strategic guidance increasing market pressures to meet earnings targets and leading managers to take real decisions that facilitate reporting earnings that allow them to meet and beat their own estimates. Second, the results obtained for informative guidance are consistent with the expectation alignment hypothesis of Ajinkya and Gift (1984). They indicate that a significant number of managers issue guidance that is informative and helps to reduce information asymmetry, which, in turn, reduces managerial incentives to engage in real earnings management to meet their earnings forecasts.

These results hold for different model specifications. They are robust to the inclusion of time- and firm- fixed effects and to clustering standard errors by firm. Results are also robust to different shock definitions and control samples.

We conduct several additional analyses to support our main results. First, we consider samples with different degrees of external monitoring. We expect that firms with lower levels of external monitoring (as measured by lower levels of analyst coverage and firms not audited by big-four audit companies) to be more prone to manage earnings. Second, we identify samples with different likelihoods of managing earnings, either because firms are suspect of manipulation or because firms can manage real earnings to a greater extent. Our main results hold across these different settings. As a final analysis, we divide our sample between low and high ability managers. We find that low ability managers engage in more real earnings management when they issue non-informative guidance, whereas the opposite is true for high ability managers. We do not find evidence that firms that stop issuing guidance change their real earnings management practices, consistent with prior research. Overall, the findings from these analyses confirm our main results that only strategic guidance creates managerial short-termism.

We make a number of contributions to prior literature. In particular, we contribute to the voluntary disclosure literature by presenting additional evidence on the relation between earnings guidance and earnings management. We extend this literature by estimating the effects of guidance on real earnings management, which has not been studied in prior literature. In doing so, we contribute to the work of Call et al. (2014), who studies the effects of short-term guidance on accruals earnings management. Our work is probably closest to that of Houston et al. (2010) and Cheng et al. (2007a), who study whether short-term earnings guidance leads to sub-optimal R&D investment and provide mixed evidence. We add to their work by considering managerial incentives to issue guidance and addressing endogeneity concerns. This permits providing novel evidence that sheds light and reconciles the mixed findings reported in prior work. Our study also contributes to the debate of whether issuing guidance fosters short-termism. We show that guidance can be informative and lead to optimal decision making (i.e., lower real earnings management). By identifying informative from strategic guidance we establish in which cases guidance is more likely to lead managers to engage in myopic behavior.

The remainder of the paper is organized as follows. Section 2 revises the relevant literature and develops the hypotheses. Section 3 contains the methodology. Section 4 describes the sample and results. Finally, Section 5 discusses the additional analyses.

1.2 Literature Review and Hypothesis Development

1.2.1 Real earnings management in response to pressures to meet earnings targets

The survey evidence in Graham et al. (2005) indicates that managers are willing to take real actions, such as postponing a new investment opportunity or reducing discretionary expending in R&D, to meet short-term earnings targets. Importantly, prior work suggests that earnings pressures originate from the firm itself as well as from markets. For example, Dichev et al. (2013) show that an overwhelming majority of surveyed CFOs (91.02%) agree that firms report earnings that misrepresent economic performance "*because there is inside pressure to hit earnings benchmarks*" (p.26). Prior empirical work validates this survey evidence and shows that managers engage in real earnings management to meet or beat earnings targets. For example, Roychowdhury (2006) finds that firms suspect of managing earnings, as defined by reporting earnings close to the zero thresholds, present unusually low discretionary expenditures and unusually high production costs. Roychowdhury interprets this result as evidence of firms managing real activities to meet earnings targets. Similarly, Gunny (2010) reports that firms just meeting earnings targets exhibit abnormally low R&D and SG&A expenses, and abnormally high production costs.

The prior empirical literature generally suggests real activities management is associated with poor future firm performance, although the evidence is somewhat mixed. Bhojraj et al. (2009) document that firms beating short-term earnings targets with low earnings quality (i.e. higher accruals and/or lower discretionary expenditures) underperform in the long-term relative to firms missing the targets with high earnings quality. In particular, low quality beaters underperform high quality missers over a 3-years period by more than 19% cumulative abnormal returns. The results in Gunny (2010) indicate that firms missing earnings benchmarks with no sign of real activities management perform better in the long term relative to firms beating or just missing zero and last year's earnings with real activities management. However, firms just meeting earnings benchmarks with real activities management have significantly higher future returns than firms not engaging in real activities management, which Gunny (2010) interprets real actions being a signal of future performance (and not opportunistic). More recently, Khurana et al. (2017) study real earnings smoothing and suggest that it destroys shareholder value in that it increases stock price crash risk.

Thus, the main body of research in this area suggests that real earnings management may lead to firm value destruction in the long-term and negative consequences for the firm. However, despite the negative effects potentially associated with real earnings management, managers must trade off many costs and benefits, both in the long- and in the short-term, and they may choose to manage earnings through real actions because, for example, missing earnings benchmarks may trigger negative price reactions, which may, in the short-term, be more costly for them (Matsumoto, 2002; Skinner and Sloan, 2002).

1.2.2 Frequent earnings guidance and managerial short-termism

While prior research does not directly address the question of whether real earnings management is associated with earnings guidance, a number of empirical and theoretical papers investigate the closely related issues of whether earnings pressures and earnings guidance creates short-termism. In the context of mandatory reporting, Gigler et al. (2014) argue that there is a trade-off between the costs and benefits of frequent reporting that affects firms' project selection. On the one hand, when there is information asymmetry between the market and firm's managers, higher reporting frequency enables prices to discipline managerial choices. On the other hand, more frequent reporting results in price pressures that induce managers to be myopic in choosing firm's investments.

Looking at earnings guidance, Cheng et al. (2007a) argue that frequent guidance exacerbates investors' and managers' focus on short-term earnings, leading to managerial myopic behavior, independent of the initial motive for issuing guidance. This is consistent with Gigler et al. (2014) idea that frequent reporting generates price pressures. In their study, Cheng et al. (2007a) examine differences in R&D investment between dedicated and occasional guiders and find that dedicated guiders invest less in R&D, meet or beat analysts' expectations more frequently and have lower long-term earnings growth rates relative to occasional guiders. Cheng et al. (2007a) consider these results as evidence of a positive relation between guidance and short-termism.[5]

However, when Houston et al. (2010) study whether the decision to stop issuing guidance is associated with increases in R&D and capital expenditures, they report contrarian evidence. This is

[5]Other papers presenting evidence and arguments supporting that earnings guidance intensifies managerial myopia include: Kasznik (1999), Degeorge et al. (1999), Bartov et al. (2002), Richardson et al. (2004), Burgstahler and Eames (2006), Acito (2011), and Koch et al. (2012).

surprising, because if it is guidance that fosters short-termism, stopping guidance should reduce managerial myopic behavior. Anecdotal evidence from managerial discussions of their decisions to stop guidance is in line with this view, as they commonly argue that stopping guidance should allow them to focus their efforts on long-term growth and to avoid short-term myopic behavior. (See Appendix A for anecdotal evidence on managerial explanations of firms' decisions to stop issuing guidance.) The results in Houston et al. (2010) suggest that after guidance terminates, the firm information environment deteriorates, mainly due to reduced analysts' coverage.[6] While this loss in coverage would likely reduce external pressures to meet earnings targets, it also potentially increases information asymmetry.

1.2.3 Earnings guidance and real earnings management

We build on the previously reviewed literature and argue that differences in the underlying incentives of managers issuing guidance may partly explain the aforementioned lack of clear evidence found in prior research, which usually considers all guidance as homogeneous.[7] These differences, in turn, are predicted to explain the extent to which managers use real earnings management to attempt to meet their own forecasts.

We base our expectations on the work of Kim and Park (2012), who argue that the formulation of guidance is associated with underlying managerial incentives, which they identify as being either associated with 'expectation management' or with 'communication incentives.' Li et al. (2011a, 2012, 2016) also recognize that guidance may be issued for different reasons and claim that treating all guidance as equal reduces the power of tests and introduces correlated omitted-variables concerns.

In particular, we classify earnings guidance as either *strategic* or *informative*. Following Kim and Park (2012), guidance is considered strategic if managers issue forecasts in an attempt to manage expectations. The ultimate aim may be to lower expectations, for example, to reduce litigation risk (Skinner, 1994; Kasznik and Lev, 1995) or to avoid missing earnings benchmarks (Matsumoto, 2002). Managers can also issue strategic guidance to manage expectations upwards to "hype" the stock price around equity offerings (Lang and Lundholm, 2000), or to trade opportunistically in their own firm's shares (Noe, 1999; Cheng et al., 2007a). In contrast, guidance is informative if it aims to reduce information asymmetries, thereby allowing managers to align market earnings expectations with their own (Ajinkya and Gift, 1984; Healy and Palepu, 2001; Dutta and Gigler, 2002), and to reduce information risks (Graham et al., 2005).

As mentioned above, this separation between informative and strategic guidance is predicted to

[6] Other papers presenting empirical evidence supporting the idea that guidance alleviates short-termism are Chen et al. (2011) and Call et al. (2014).

[7] See Hirst et al. (2008) for a review of the literature on management earnings forecasts.

explain the extent to which short-term earnings guidance leads to real earnings management. In particular, firms issuing informative guidance are expected to be primarily concerned with reducing information asymmetries between insiders and outsiders. For managers in these firms, target beating would either not be a concern, or it would be a second order concern relative to the concern of reducing information asymmetry. Given this, and also, that real earnings management deteriorates the information environment and obfuscates the earnings signal (Kothari et al., 2016; Khurana et al., 2017), managers issuing informative guidance are predicted to have limited incentives for real earnings management. Further, because informative guidance is intended to fill in the information gaps present in the market and to improve the firm information environment (Balakrishnan et al., 2014), informative guidance is likely to result in a reduced need to rely on earnings management to meet relevant earnings benchmarks.

Prior research is consistent with the above ideas that not all managers are equally concerned with earnings targets (Graham et al., 2005; Dichev et al., 2013), and also, that markets 'see through' target beating behavior and apply different penalties and rewards to target missers and beaters, depending on the levels of real earnings management underlying their target beating strategies (Bhojraj et al., 2009; García Osma and Young, 2009).

In contrast, firms issuing strategic guidance are expected to be primarily concerned with meeting earnings targets. Managers in these firms are predicted to prioritize expectations management and to take additional measures (such as engaging in real earnings management practices or issuing additional earnings guidance) to ensure their forecasts are met. Perversely, in these firms, issuing a misleading earnings target represents a commitment to subsequently meet it, and thus, guidance serves to increase the internal and external (market) pressures faced by managers to meet their own forecasts (Cheng et al., 2007a). It is also likely that strategic guidance, if assessed to not be informative, may create greater uncertainty among analysts, potentially moving analysts' consensus forecast further away from managerial targets, after the forecast is issued. Therefore, managers issuing strategic guidance are likely to be caught in a game of expectation management that may lead them to engage in real earnings management.

To summarize, when managers issue informative guidance, we expect them to engage in less real earnings management relative to managers issuing non-informative or strategic guidance. This leads us to our main hypothesis:

> **H1:** *Real earnings management is greater (lower) in firms issuing strategic (informative) short-term earnings guidance.*

1.3 Methodology

1.3.1 Real Earnings Management Measure

We construct our proxy for real earnings management (REM) following Roychowdhury (2006) and Zang (2012). These studies use deviations from normal levels of discretionary expenditures and production costs to detect overproduction and opportunistic cuts in discretionary expenditures. Following Zang (2012), we use abnormal production costs minus abnormal discretionary expenditures as an aggregate measure of real earnings management.[8]

To construct our proxy, we first estimate the following models within each fiscal year and two digits SIC industry, using quarterly data:

$$\begin{aligned}\frac{PC_{i,t}}{A_{i,t-4}} =&\alpha_0 + \alpha_1(\frac{1}{A_{i,t-4}}) + \alpha_2 Q_{1i,t} + \alpha_3 Q_{2i,t} + \alpha_4 Q_{3i,t} + \alpha_5 Q_{4i,t} \\ &+ \alpha_6(\frac{\Delta S_{i,t}}{A_{i,t-4}}) + \alpha_7(\frac{\Delta S_{i,t-4}}{A_{i,t-4}}) + \epsilon_{i,t}\end{aligned} \tag{1.1}$$

$$\begin{aligned}\frac{DE_{i,t}}{A_{i,t-4}} =&\alpha_0 + \alpha_1(\frac{1}{A_{i,t-4}}) + \alpha_2 Q_{1i,t} + \alpha_3 Q_{2i,t} + \alpha_4 Q_{3i,t} + \alpha_5 Q_{4i,t} \\ &+ \alpha_6(\frac{\Delta S_{i,t}}{A_{i,t-4}}) + \epsilon_{i,t}\end{aligned} \tag{1.2}$$

where subscript i indexes firms and t indexes calendar quarters. Production costs ($PC_{i,t}$) are defined as the change in inventory from quarter $t-4$ to t plus the cost of goods sold in quarter t, A_{t-4} is the amount of total assets in quarter $t-4$, S_t are sales in quarter t. Discretionary expenditures ($DE_{i,t}$) are defined as the sum of advertising, R&D and SG&A expenditures in quarter t. Following Collins et al. (2014) we include fiscal quarter dummies $Q1_{i,t}$ to $Q4_{i,t}$ to capture fiscal quarter effects and calculates changes in sales relatives to the same quarter of the previous year, to avoid seasonality effects. We require at least 15 observations to perform each estimation. Abnormal levels of production costs ($AB\_PC_{i,t}$) and abnormal discretionary expenditures ($AB\_DE_{i,t}$) are measured as the residuals of models (1) and (2) respectively. Higher values of $AB\_PC_{i,t}$ indicate more REM while higher values of $AB\_DE_{i,t}$ indicate lower REM. Therefore, we define our proxy for REM as the sum of $AB\_PC_{i,t}$ and negative $AB\_DE_{i,t}$. Thus, positive (negative) values of REM indicate income-increasing (income-decreasing) earnings management. Appendix B provides further details on the estimation of our these

[8] Roychowdhury (2006) also creates a measure for abnormal cash flows. We do not consider it because it is affected in opposite directions by real activities manipulations and the overall effect might be ambiguous (Roychowdhury, 2006; Zang, 2012).

proxies.

1.3.2 Identification Strategy

A major concern in studying the effects of guidance on short-termism is the fact that the decision to issue guidance is likely endogenous. The reasons that lead managers to voluntary disclose more information might be related with their decision to manage real earnings. This creates a potential correlated omitted-variable problem, leading to biased and inconsistent OLS estimators. Another related issue is the fact that, as we have discussed in detail in our hypothesis development section, not all guidance is equal. Treating all guidance as equal may strengthen endogeneity problems.

To mitigate these concerns, we exploit exogenous decreases in analyst coverage due to brokerage closure as a shock to the firm information environment.[9] Kelly and Ljungqvist (2012) argue that brokerage decisions to close research operations are related with industry trends, regulatory changes, and strategic reasons not related with fundamentals of the companies they cover. Therefore, coverage terminations related with brokerage closure are likely to be exogenous to firms' fundamentals. Using a difference-in-difference approach, Kelly and Ljungqvist (2012) show that exogenous terminations lead to an increase in treated firms' information asymmetry. Firms that experience this exogenous decrease in analyst coverage show an increase in bid-ask spreads, higher values of the Amihud illiquidity measure, larger number of missing-return days, more volatile returns around earnings announcements, and greater earnings surprises relative to control firms.

Importantly, prior research shows that this shock to analyst coverage triggers managerial informative guidance. Anantharaman and Zhang (2011) find that firms suffering an exogenous shock to analyst coverage react by increasing guidance, and show evidence of subsequent increases in analyst coverage after the guidance response. This is consistent with exogenous decreases in analyst coverage being more likely to revert, relative to endogenous decreases (i.e., those related with firm performance). In the same vein, the evidence in Balakrishnan et al. (2014) confirms that managers respond to exogenous coverage shocks by increasing voluntary disclosure, and establish a positive causal link between guidance and liquidity. Taken together, these results are consistent with the idea that managers value analyst coverage, and with guidance being an effective managerial tool to shape the firm information environment.

We build on this prior evidence and identify as informative those management forecasts made in response to an exogenous reduction in analyst coverage. To measure exogenous shocks to analyst

[9] An early paper using this identification strategy is Yu (2008). Other papers exploiting the same idea are: Hong and Kacperczyk (2010); Anantharaman and Zhang (2011); Irani and Oesch (2013); Balakrishnan et al. (2014); Chen et al. (2015).

coverage, we follow a modified Yu (2008) procedure as in Anantharaman and Zhang (2011). According to Yu (2008), the probability that a particular broker continues to cover a firm after a reduction of its size gives the expected coverage for the firm of that broker. By aggregating over all the brokers covering the firm we obtain the expected number of analysts covering it. Expected coverage is not affected by the endogeneity concerns that affect realized coverage because it is a measure of the tendency to keep the coverage before a broker decides which firm to keep (Yu, 2008). An important assumption we have to make to obtain the expected coverage for a particular firm in a given quarter is that brokerage firms assign the same amount of resources to covering a given firm i in quarter t. Then, if firm i is covered by j brokers in quarter $t-1$, following Anantharaman and Zhang (2011) the expected coverage of firm i from broker j in quarter t ($EC_{i,j,t}$) is:

$$EC_{i,j,t} = min\{\frac{Broker\_Size_{j,t}}{Broker\_Size_{j,t-1}} * Coverage_{i,j,t-1}, 1\} \tag{1.3}$$

where $Broker\_Size_{j,t}$ is the number of analysts working for broker j in quarter t, and $Coverage_{i,j,t-1}$is the number of analysts in broker j covering firm i in quarter $t-1$. $EC_{i,j,t}$ has a minimum value of 1, because data shows that within brokers each stock is covered only by one analyst. As a result, expected coverage of firm i in quarter t ($EC_{i,t}$) is:

$$EC_{i,t} = \sum_j EC_{i,j,t} \tag{1.4}$$

starting from (4), we obtain changes in analyst coverage as the difference in the number of analyst following firm i after quarterly earnings announcement ($COV_{i,t}$) between period t and $t+1$. For those firms with a decrease in coverage, an exogenous decrease ($EXO\_Chg_{i,t}$) is given by the difference between $EC_{i,t}$ and $COV_{i,t}$ (see Figure 1).

1.3.3 Research Design

To test the relation between guidance and real earnings management, we estimate the following simple panel data model:

$$\begin{aligned} REM_{i,t} = & \alpha + \beta_1 GUIDE_{i,t} + \beta_2 SHOCK_{i,t} + \beta_3 GUIDE_{i,t} SHOCK_{i,t} \\ & + \sum_{k=1}^{12} \theta_k Controls_{i,t-4} + TimeFE + FirmFE + \epsilon_{i,t} \end{aligned} \tag{1.5}$$

where $GUIDE$ is a dummy variable equal to one if the firm issues guidance in a particular quarter and zero otherwise. We exclude all guidance made more than 90 days before the quarter-end, because we want to focus in short-term quarterly forecasts and avoid including stale forecasts in our sample. We also exclude all quarterly forecasts made after the quarter-end because these forecasts are likely to be earnings pre-announcements. $SHOCK$ is a dummy variable indicating whether the firm suffers an exogenous shock to analyst coverage in quarter t, it takes value one when $EXO\_Chg_{i,t}$ is negative and zero otherwise.

Under H1, we expect β_1 to be positive and β_3 to be negative. Accordingly, if the exogenous decrease in analyst coverage deteriorates the firm information environment β_2 should be positive. Time- and firm- fixed-effects are included to control for time-trends or shocks that affect all firms in the sample and unobservable firm-specific time-invariant characteristics respectively.

We follow prior literature to control for other determinants of real earnings management. We control for past discretionary accruals (D_ACC) as a proxy for constraints in future earnings management (Koch et al., 2012), analyst coverage (AF) as a proxy for the role of analyst as external monitors (Healy and Palepu, 2001; Yu, 2008), institutional ownership ($INST$) because more sophisticated investors might understand long-term value implications of managerial actions (monitoring role) and discourage real activities manipulations (Bushee, 1998; Roychowdhury, 2006), leverage (LEV) as a proxy for the presence of debt covenants, firms might manage real activities to avoid violating the covenants (Roychowdhury, 2006; DeFond and Jiambalvo, 1994), book to market ratio (BTM) as a proxy for growth opportunities, growth firms have more incentives to manage earnings (Skinner and Sloan, 2002), for operating cycle ($OPCYCLE$) as a proxy for the flexibility in real activities management (Roychowdhury, 2006), capital intensity ($CAPINT$) as a proxy for reporting quality (Cohen, 2006). In addition we include the typical controls used by previous research firm size ($SIZE$), performance (ROA), volatility of the firms' operating environment (S_CFO) and earnings persistence ($PERS$) and earnings predictability ($PRED$). Our control variables are lagged four quarters in order to control for seasonality and to avoid possible effects that $GUIDE$ and REM might have on the controls. Appendix C provides definitions for all variables.

1.4 Sample and Results

Our sample is composed of US publicly-listed firms and covers the period 2003-2013. We start in 2003, after the passage of Reg. FD and SOX, because these regulations had an impact on firms' guidance and earnings management behavior. Additionally, we exclude all firms that might be subject to specific institutional and regulatory constraints (SIC codes 44-49 and 60-69).

We obtain guidance data from I/B/E/S Guidance database, quarterly financial data from Compustat, analyst coverage from I/B/E/S, and institutional ownership information from Thomson Reuters 13F. We drop firm-quarter observations with missing values in Compustat and with negative total assets and negative sales. After imposing all data requirements for the estimation of model (5), our final sample consist of 32,841 firm-quarter observations. Continuous variables are winsorized at the 1% and 99% to mitigate concerns regarding outliers.

Over three thousand firms issued quarterly earnings guidance during the period 2003-2013.[10] In our final sample, 22% of firm-quarters are quarters in which firms issue guidance. Table 1 Panel A shows how the number of firms issuing guidance decreases considerably during the sample period. In 2003 firms covered by I/B/E/S Guidance represent about 15% of Compustat universe while they represent only 7.47% by 2013. This data is consistent with the discussed claims from practitioners to end guidance and with anecdotal evidence reported in Appendix A showing that firms report terminating guidance to avoid myopic behavior.

Table 1 Panel B presents summary statistics for the variables used in model (5). Mean (median) REM is 8.73% (6.45%) and a mean (median) discretionary accruals is 1.6% (-2.1%). A mean (median) firm in the sample has 5.61 (3) analyst following (see Appendix C for variables definitions). Table 1 Panels C and D show average values by whether or not firms issue guidance ($GUIDE$), and whether or not firms experience an exogenous decrease in analysts forecasts ($SHOCK$). On average, guiding firms have higher discretionary accruals and greater analyst coverage. They also have a higher proportion of institutional ownership, and greater return on assets. In addition, shocked and non-shocked firms differ along several observable characteristics. Shocked firms have higher discretionary accruals, more analyst coverage, higher institutional ownership, larger size, higher leverage, larger capital intensity, higher return on assets, higher earnings persistence and less earnings predictability (Table 1 Panel D).[11] Table 1 Panel E shows correlation coefficients between our measure of real earnings management and firm observable characteristics.

Table 2 shows the results of the estimation of model (5). All models contain firm fixed effects. Column 1 report regression results of a naïve OLS model, without considering endogeneity or differences in guidance. The coefficient on $GUIDE$ is positive and significant. Columns 2-5 show the results of the regressions after including the exogenous shock to analyst coverage, and using different model specifications. Columns 2 and 3 present the results for the estimation of equation (5) with year

[10] This represents around 20% of Compustat universe and 30% of I/B/E/S coverage for firms issuing earnings guidance during that period.

[11] Untabulated results indicate that differences in mean and median values are statistically significant at the 1% level.

fixed-effects and with quarter fixed-effects respectively. Across the two specifications we find a positive and significant coefficient on $GUIDE$ and $SHOCK$, and a negative and significant coefficient on the interaction between $GUIDE$ and $SHOCK$.[12]

A negative coefficient on the interaction term indicates that informative guidance causes a reduction on income-increasing real earnings management. A positive coefficient on the guidance term suggest that strategic guidance increase real earnings management.

Our intention is to identify guidance made in response to an exogenous shock in analyst coverage, but our research design does not allow us to identify the exact date of the shock. To ensure that we capture guidance made in response to the shock, we split the interaction term between early (i.e., guidance made before previous quarter earnings announcement) and late guidance (i.e., guidance made after previous quarter earnings announcement). We expect guidance made later in the quarter to be more likely in response to the shock relative to guidance made early in the quarter. Table 2 Column 4 presents the results of estimating equation (5) partitioning the interaction term between early and late guidance. As expected, the estimated coefficient on the interaction term for guidance made later in the period is negative and statistically significant, while for early guidance is not significant. Estimated coefficients on $GUIDE$ and $SHOCK$ remain positive and significant as in previous specifications.[13]

Our results reconcile mixed evidence found by previous literature on the effects of guidance on short-termism. The negative and statistically significant estimated coefficient on the interaction term between $SHOCK$ and $GUIDE$ is consistent with Houston et al. (2010) who find no evidence of higher R&D and capital expenditures after guidance cessation and support our hypothesis that informative guidance reduces real activities manipulation. In turn, the positive and significant coefficient on $GUIDE$ suggest that non-informative guidance is positively associated with real earnings management, consistent with previous literature claims that guidance increases managers' pressure to meet self-imposed earnings targets.

A key element of our paper is the shock that allows us to identify informative guidance and it could be possible that our results are driven by the definition of the shock. To rule out this possibility we estimate equation (5) for different SHOCK sizes (i.e. exogenous decrease in analyst coverage relative to the level of coverage), the results of this analysis are reported in Table 3. An interesting result is that the coefficient on the interaction term remains negative and significant, and is monotonically

[12]Results are qualitatively similar in sign and significance if we use absolute real earnings management as dependent variable.

[13]In untabulated results we estimate the probability of issuing guidance in a given quarter using a probit model. We use as independent variables the first four lags of $GUIDE$, $SHOCK$ and the first three lags of $SHOCK$, and lagged four values of BTM, SIZE, LEV, AF. We find that first lagged value of $SHOCK$ is positive and significant in determining the probability of issuing guidance in quarter t, consistent with managers responding to shocks in the information environment by issuing guidance.

increasing in the severity of the shock up to certain point. Meaning that the effect of an informative guidance is stronger when the shock is more severe. When the definition of the shock includes only extreme shocks ($EXO\_DEC > 60\%$) estimation results are statistically insignificant. A possible explanation is that for extreme shocks (e.g. a company followed by 3 analysts that lost coverage of 2 analysts), the worsening in firms' information environment is less likely to be reverted by guidance. Finally, if we define shocked firms as those suffering an exogenous decrease up to 60% of their coverage ($0\% < EXO\_DEC < 60\%$) our results are similar to those presented in Table 2 column 3.

An additional concern is that guiding firms and non-guiding firms might be different in unobservable characteristics and this can be driving our results. To mitigate this concern we estimate model (5) using as control sample non-guidance quarters of guiding firms. Table 4 column 1 presents the estimation results. We obtain a positive and significant coefficient on $GUIDE$ and a negative and significant coefficient on $GUIDE\_SHOCK$, consistent with the main results presented in Table 2 column 3. Another factor that might influence our results is the fact that our shock may be affecting a particular set of firms. Because systematic differences between treatment and control samples might be correlated with our dependent variable, we built our control sample using a nearest-neighbor propensity score matching methodology. We match firms in size, performance, leverage, book-to-market and analyst coverage in the quarter before the shock. For an observation to be in the control sample we also require to be in the same industry-quarter as the treated nearest-neighbor. We implement the propensity score matching using a nearest-neighbor logit regression without replacement using a standard tolerance (0.005 caliper). Table 4 column 2 shows that our coefficient on $GUIDE\_SHOCK$ remains negative and statistically significant. Table 4 panel B present the balance properties of the propensity score matching.

As an additional robustness check Table 4 column 3 presents the results of a placebo test. We generate a random shock replicating the proportion of shocked firms in our sample and estimate model (5), as expected estimated coefficients for the $SHOCK$ and the interaction term are not statistically significant. While for $GUIDE$ the coefficient is positive and significant as in the naïve model presented in Table 2 column 1.[14]

[14] The results in Table 5 column 3 are from one realization of the random shock. Untabulated results indicate that Fama-MacBeth coefficients of estimating model (5) using one thousand different realizations of the random shock are similar in sign and significance.

1.5 Additional Analysis

In this section, we provide additional evidence supporting our main results by examining a number of contexts where we expect the effects of guidance on real earnings management to be stronger. In particular, we focus on settings where firms are more likely to manipulate, the ability of managers is higher or the information environment is poor. These are settings where the effects of the shock are more severe and thus, the benefits of issuing informative guidance are higher.

1.5.1 External Monitoring

Highly monitored managers have fewer opportunities to manage earnings. Analysts play a role as external monitors of the firm and might constrain firms' earnings management behavior. This is because analysts keep track of earnings numbers regularly and their financial expertise and industry background can help to uncover cases of fraud or detect unusual earnings numbers (Healy and Palepu, 2001; Dyck et al., 2010; Yu, 2008). Additionally, Big 4 audit firms can also deter earnings management because they are likely to do a better auditing job relative to small audit firms either because they are more experienced, have more resources or a reputation to maintain (DeFond and Jiambalvo, 1991, 1993; Becker et al., 1998; Francis et al., 1999).

If monitoring alleviates short-termism we expect our results to be weaker for firms subject to high monitoring and stronger for firms with low monitoring. To test this prediction we split our sample between firms with low/high analyst coverage and firms audited by a big 4/non-big 4 auditor. Table 5 present the results of estimating equation (5) for samples with different monitoring. As expected for firms with low monitoring (i.e. low analyst coverage/non-big 4 auditor) the coefficient on GUIDE is positive and statistically significant while the coefficient on the interaction between GUIDE and SHOCK is negative and significant. Besides, for firms with low analyst coverage the shock to the information environment is likely to be more severe, consistently the coefficient on SHOCK is positive and significant. On the other hand for high monitoring firms (i.e. high analyst coverage/big 4 auditor) all the coefficients of interest are not significant.

Supporting our hypothesis we find that for firms with higher external monitoring, that are expected to engage in less earnings manipulation there is no difference in real earnings management among informative and strategic guidance. While for firms with low external monitoring, where we expect more earnings manipulation, we find that informative guidance reduce real earnings manipulations and strategic guidance increase manipulation.

An additional explanation of this results is that having more analyst coverage and a big 4 auditor implies a better firm information environment ex-ante, therefore the effect of the shock is weaker and the benefits from issuing an informative guidance are lower. While for firms with an ex-ante worse information environment the effect of the shock is stronger and the benefits of issuing an informative guidance are potentially higher.

1.5.2 Likelihood of Real Earnings Manipulation

Previous literature indicates that firms just meeting/beating earnings benchmarks are more likely to engage in earnings management (Burgstahler and Eames, 2006; Degeorge et al., 1999; Bartov et al., 2002; Graham et al., 2005). Focusing in a setting in which firms are suspect of manipulating earnings increase the power of our test. Therefore, if suspect firms are more likely to manipulate earnings, we expect the effects of strategic guidance to be stronger among suspect firms, and the effect of informative guidance to be stronger among non-suspect firms. Following, Roychowdhury (2006) and Zang (2012) we define a dummy variable for firm-quarters suspect ($SUSPECT$) of manipulation. $SUSPECT$ takes value one if quarterly earnings before extraordinary items over lagged total assets is between 0 and 0.002 (i.e. firms just meeting/beating zero earnings), change in EPS excluding extraordinary items from same quarter last year is between 0 and 2 cents (i.e. just meeting/beating last-year earnings), or earnings surprise is between 0 and 2 cents (i.e. just meeting/beating analyst forecast) and zero otherwise.

Table 6 columns 1 and 2 present the results of estimating equation (5) separately for suspect and non-suspect firms. As expected, $GUIDE$ is positive and significant for suspect firms, and four times larger than for non-suspect firms. While the interaction $GUIDE\_SHOCK$ is not significant for the sample of suspect firms and it is negative and significant for non-suspect firms.

As a further check, we focus in another setting where firms are likely to manage earnings and split our sample between consistent and non-consistent target beating firms. We define $CONS\_BEAT$ as a dummy variable equal to one if the firm meet/beat the above mentioned earnings benchmarks in the past four quarters and zero otherwise. Table 6 columns 3 and 4 present the results of estimating equation (5) for consistent and non-consistent beaters. $GUIDE$ is positive and significant for both samples, but as expected is greater for suspect firms. The interaction $GUIDE\_SHOCK$ is negative and significant for both samples.

Finally, we split our sample among manufacturing and non-manufacturing firms. According to Roychowdhury (2006) manufacturing firms have more strategies available for real actions management. Therefore, our results should be stronger for manufacturing firms. Following Roychowdhury (2006) we define a dummy variable equal to one if the firm belongs to a manufacturing industry (i.e. two-digit SIC code between 20 and 39) and zero otherwise. Table 6 column 5 and 6 present the results of estimating equation 5 for manufacturing and non-manufacturing firms. As expected, $GUIDE$ is positive and $GUIDE\_SHOCK$ is negative for both samples. The results are only statistically significant for the sample of manufacturing firms.[15]

1.5.3 Financial Constraints

Managers in financially constrained firms have lower incentives to manage real earnings because the costs of deviating from optimal business practices might be too high if the objective of the manager is to improve firm's operations (Zang, 2012). Moreover, if financially constrained firms need to raise external capital to finance investment decisions, the higher scrutiny from capital markets will more likely deter managers from investing sub optimally. However, managers of firms with poor financial conditions will have higher incentives to issue overly optimistic forecasts, as an attempt to increase firm value perceptions due to career concerns or implicit contracts (Koch, 2002). In line with our main prediction we expect the coefficient on $GUIDE$ to be positive for financially constrained firms, and the coefficient on the interaction $GUIDE\_SHOCK$ to be negative for non-financially constrained firms. We use Farre-Mensa and Ljungqvist (2016) probability of default (PD) measure to split our sample among financially constrained and non-financially constrained firms. We consider a firm to be financially constrained if PD is greater than 20%. Table 6 columns 7 and 8 present the results of this analysis, as expected we get a positive and significant coefficient on $GUIDE$ for financially constrained firms and a negative and significant $GUIDE\_SHOCK$ for non-financially constrained firms.

1.5.4 Managerial Ability

High ability managers are more likely to issue accurate forecasts relative to low ability managers (Feng et al., 2009). Therefore, low ability managers may engage in more real earnings management after issuing guidance because this guidance is more likely to be inaccurate (independent of managerial incentives). While for high ability managers we expect informative guidance to decrease real activities manipulation, not only because is informative but also because it is more likely to be accurate. We use Demerjian et al. (2012) measure of managerial ability to split our sample between low ability and high ability managers. Their measure is a score rank (MA_SCORE) between zero and one based on managers' efficiency in generating revenues, where one is the highest ability. We consider a firm to

[15] In untabulated analysis we further consider whether firms in different industries (i.e. manufacturing vs. service) rely on different real earnings management strategies but we do not find any meaningful difference.

have a high (low) ability manager if MA_SCORE is above (below) the median value of the sample.[16] Table 7 present the results of estimating equation (5) for samples with different managerial ability. As expected, for low ability managers the coefficient on $GUIDE$ remains positive and significant and for high ability managers $GUIDE\_SHOCK$ remains negative and significant.

1.5.5 Guidance Frequency and the Decision to Stop Guidance

Cheng et al. (2007a) claim that frequent short-term guidance exacerbates short-termism. To see how guidance frequency might affect our results we condition our analysis on firms' quarterly guidance frequency. Following Cheng et al. (2007a) we measure frequency (FREQ) using the deciles of industry guidance frequency distribution. We split our sample in Low FREQ (firm-quarters in deciles 1 to 4), Mid FREQ (firm-quarters in deciles 5 to 7) and High FREQ (firm-quarters in deciles 8 to 10).

If short-term guidance foster short-termism, the decision to stop guidance should lead to less myopic behavior, and as suggested by anecdotal evidence (see APPENDIX-A) the effect should be higher for frequent guiders that are supposedly the ones subject to higher market pressures ex-ante. We identify those firms that stop issuing quarterly guidance in our sample, and whether it happens after an informative guidance (STOP_INFO) or an strategic guidance (STOP_STRATEGIC).

Table 8 present the results of estimating model (5) conditioning on frequency and including control variables for the decision to stop guidance. Our main results hold for Low FREQ and Mid FREQ samples. For High FREQ sample coefficients are not significant, indicating that for high frequent guiders there is no difference in income increasing real earnings manipulation between guiding and non-guiding quarters. Until now we only consider informative guidance as those guidance made in response to a shock in the information environment of the firm, but managers that are committed to issue credible short-term guidance will do it even if the firm do not suffer a shock to the information environment. Frequent guidance capturing informative short-term guidance is a possible explanation for not finding any significant difference between GUIDE and GUIDE_SHOCK for frequent guiders.

Regarding the decision to stop guidance, the only case in which this decision leads to lower income increasing real earnings manipulations is when this decision is made by infrequent guiders and after an strategic guidance. Contrary to the arguments present in the anecdotal evidence, the decision of frequent guiders to stop guidance do not reduce real earnings management in subsequent periods. Moreover, the sign on the coefficient of STOP_INFO is positive in all cases although is not statistically significant.

[16] Estimation results remain similar if we use mean value or top and bottom quintiles of MA_SCORE to split our sample across managerial ability.

1.6 Summary and Conclusions

We study if quarterly earnings guidance causes managerial short-termism, in the form of real earnings management. We exploit an exogenous shock to firms' information environment to distinguish between informative and strategic management short-term earnings guidance, and find that informative guidance leads to less real earnings management in contrast to strategic guidance that increases real earnings management. In cross-sectional analyses, we find that our results are stronger for firms with worst external monitoring, firms non-suspect of manipulating earnings, firms in manufacturing industries, non-financially constrained firms, and firms whose managers have high ability.

We interpret this result as informative (strategic) guidance alleviating (worsening) short-termism. First, this is consistent with the expectation alignment hypothesis of Ajinkya and Gift (1984) where guidance helps to reduce information asymmetries and reduce the need of managers to engage in real earnings management to meet earnings targets. Second, our results are also consistent with non-informative guidance increasing market pressures to meet earnings targets and leading to higher levels of real earnings management. In line with survey evidence presented by Graham et al. (2005).

Our study responds to calls for research on the consequences of frequent reporting of results, as concerns exists that frequent reporting may lead to managerial short-termism and thus, to inefficient decision-making, reconciling prior mixed evidence (Kasznik, 1999; Degeorge et al., 1999; Bartov et al., 2002; Richardson et al., 2004; Burgstahler and Eames, 2006; Houston et al., 2010; Koch et al., 2012). Our results suggest that whilst some guidance may indeed be associated with sub-optimal managerial decision-making, not all guidance has this negative consequence.

APPENDIX A- Anecdotal Evidence on Firms Guidance Decisions

Company Guidance Decision Rationale

Source - [Manager Discussing Rationale]

The Coca-Cola Company

Q3-2002 Earnings Conference Call - [Gary Fayard - CFO and Sr. Vice President]

Q: Andrew Conway - CSFB

"as you mentioned, it's early to talk about 2003 but (...), is it reasonable to think that management would widen the range of expectations for global volume for '03 closer to (...). How do you triangulate your long-term views when we have a period of short-term macro effect?"

A: Gary Fayard

"I'm going to dodge the question, however, only because truly we are in the midst in the process and premature to give guidance on it. Let me say that we are still committed to the long-term growth of this business (...) We'll continue to manage the business for the long-term and as we go through the business planning process, as we complete that, we'll give you a full update on the expectations for next year later this fall."

Q: Caroline Levy - UBS Warburg

"I'm trying to understand how you managed to achieve your third quarter estimates in the face of all the economic challenges that exist and yet will not or do not expect to achieve your fourth quarter (...) any guidance you could give on that, because I think that's what everybody is confused about."

A: Gary Fayard

"Let me give a shot at that one. First the following, if we step back and look at the full year first and let me address it that way first. Because as you know, we give guidance on full year but not, we do not give any quarterly guidance (...)"

Q3-2002 Earnings Conference Call - [Gary Fayard - CFO and Sr. Vice President]

"A couple of things about the release this morning (...) number one, we are as committed as ever to our long-term growth objectives in both volume and profit.(...) Number two (...) we will no longer provide guidance after today about earnings. We believe it will allow the company to continue to focus on long-term growth objectives, which is good for our shareholders and not managed in the short-term quarter-to-quarter"

Q4-2002 Earnings Conference Call [Gary Fayard - CFO]

"Now, turning to the current year, as we stated in December, we are not going to give specific earnings per share guidance for quarters or for the full year (...)"

(continue on next page)

APPENDIX A- *(continued)*

IDEXX Laboratories Inc.

Q3-2005 Earnings Conference Call - [Merilee Raines - CFO]

"I want to mention that we will be making a change to our communications regarding financial guidance beginning next year.(...) When we update our guidance for 2006 at the time of our 2005 fourth quarter earnings release, we will be focusing our projections on the total year, and we will therefore not give guidance for the first quarter of 2006. As the year progresses, we will continue to express guidance in terms of the full year rather than on a quarter-by-quarter basis.(...) We're making this change, not as a result of any change in our outlook for the business, but because this approach is consistent with the way that we manage the business, which is not to focus on single quarterly results but to maximize long-term value creation for our shareholders."

Q4-2005 Earnings Conference Call - [Merilee Raines - CFO]

"Now, looking forward to 2006. As we mentioned in our third quarter earnings call, we will be giving only annual guidance for 2006 (...)"

Google Inc.

Q1-2005 Earnings Conference Call - [Eric Schmidt - CEO]

"Our focus remains very, very clearly and steadfastly on the long-term growth (...). We are going to continue our long-standing policy of not providing forward guidance (...) And I would also encourage you not to rely on any estimated metric that you hear to try to formulate how our business works (...) no single estimate of metric is a very good precise predictor of how we're doing (...)"

Q1-2006 Earnings Conference Call - [Eric Schmidt - CEO]

"We also – of course, there's been a lot of debate about this – are going to continue to not give forward guidance, as per our long-term policy(...)"

APPENDIX B- Real Earnings Management Measure Estimation

This appendix explains the estimation of our proxy of real earnings management. Following Roychowdhury (2006) and Zang (2012), we start from the entire population of COMPUSTAT for the period 2002-2014. We exclude financial and regulated industries (SIC 6000-6999 & SIC 4400-5000). Then to avoid possible mistakes in the database we remove all observations with missing (negative) values of total assets (COMPUSTAT item atq), sales (item saleq) and selling, general and administrative expenses (SG&A) (item xsgaq). We also exclude all observations with missing values of: common equity (item ceqq), net income (loss) (item niq), cost of goods sold (item cogsq), inventory (item invtq), and income before extraordinary items (item ibq).

Production cost ($PC_{i,t}$) are defined as the same of cost of goods sold (COMPUSTAT item cogsq) plus change in inventory (item invtq). Discretionary expenditures ($DE_{i,t}$) are defined as the sum of research and development expenses (R&D) (item xrdq) and SG&A expenses (item xsgaq). R&D expenses are set equal to zero if they are missing in COMPUSTAT and SG&A expenses are available. A_t is the value of total assets of quarter t (item taq) and S_t are the sales of the quarter (item saleq). Finally $Q1_{i,t}$ to $Q4_{i,t}$ are fiscal quarter dummies, i.e. $Q1_t$ would be equal to 1 for fiscal quarter 1 and zero otherwise (using COMPUSTAT item datafqtr).

Table B.1, panel A report the estimation results of models (1) and (2). The models are estimated cross-sectionally within each fiscal year and two digits SIC industry using quarterly data. There are 598 industry-years during the sample period and on average the number of observations for each regression is greater than 260. The mean adjusted R2 is 77.71 percent for the production costs model and 40.29 percent for the discretionary expenditures model. For both models the estimated coefficients are comparable in magnitude and significance to those reported in the annual models by Roychowdhury (2006) and Zang (2012). Panel B shows summary statistics for the estimated proxies of real earnings management. The residuals from equations (1) and (2) measure abnormal levels of production costs ($AB\_PC_{i,t}$) and discretionary expenditures ($AB\_DE_{i,t}$) respectively. According to Roychowdhury (2006) managers can boost reported earnings by overproducing which will be reflected in positive values of $AB\_PC_{i,t}$, or by cutting discretionary expenditures which that are going to be associated with negative values of $AB\_DE_{i,t}$. Following Zang (2012) we define real earnings management as $REM_{i,t} = AB\_PC_{i,t} - AB\_DE_{i,t}$. $REM_{i,t}$ indicates the total level of real earnings management. Correlations among the proxies of real earnings management are reported in panel C.

Table B.1

Measurment of Real Activities Manipulation 2002-2014

Panel A: Estimation of the Normal Levels of Production Costs and Discretionary Expenditures[a]

Production Costs		**Discretionary Expenditures**	
Intercept	-0.0131***	Intercept	0.0322***
$1/A_{t-4}$	0.0437	$1/A_{t-4}$	1.2392***
Q_{1t}	0.001	Q_{1t}	-0.0003
Q_{2t}	-0.0007	Q_{2t}	-0.0006
Q_{3t}	0.0066	Q_{3t}	-0.0017***
Q_{4t}	0.0068	Q_{4t}	0.0040***
St/A_{t-4}	0.7212***	$St-4/A_{t-4}$	0.1432***
$\Delta S_t/A_{t-4}$	-0.0989*	-	-
$\Delta S_{t-4}/A_{t-4}$	0.2661	-	-
Mean Adj. R2 (%)	77.71	Mean Adj. R2 (%)	40.29
Mean # of Observations	263.32	Mean # of Observations	263.32
# of industry-years	598	# of industry-years	598

Panel B: Summary Statistics for Real Activities Manipulation Measures

Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**25%**	**75%**
AB_PC_t	170528	0.00029	-0.00284	0.08431	-0.03903	0.03468
AB_DE_t	170528	-0.00321	-0.01101	0.08333	-0.04552	0.01931
REM_t	170528	0.00326	0.00953	0.13972	-0.05102	0.07215

Panel C: Pearson (Lower Triangle) and Spearman (Upper Triangle) Correlations

	AB_PC_t	AB_DE_t	REM_t
AB_PC_t		-0.3647***	0.8194***
AB_DE_t	-0.3024***		-0.7673***
REM_t	0.7941***	-0.7947***	

[a]Following Roychowdhury (2006) and Zang (2012), regressions are estimated cross-sectionally for each industry-year for the period 2002-2014 using quarterly data. Two-digit SIC code industry grouping is used. Each model is estimated for industry-years having at least 15 observations. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels.

APPENDIX C - Variable Definitions

Construct	Proxy	Name
Discretionary Accruals	Discretionary accruals for quarter t are defined as total accruals minus normal accruals derived from a modified Jones Model (Jones, 1991). Following Dechow et al. (1995) and Collins et al. (2014) the model for quarterly normal accruals is specified as: $\frac{ACC_{i,t}}{A_{i,t-4}} = \alpha_0 + \alpha_1(\frac{1}{A_{i,t-4}}) + \alpha_2 Q_{1i,t} + \alpha_3 Q_{2i,t} + \alpha_4 Q_{3i,t} + \alpha_5 Q_{4i,t} + \alpha_6(\frac{\Delta S_{i,t}}{A_{i,t-4}}) + \alpha_7(\frac{PPEi,t}{A_{i,t-4}}) + \epsilon_{i,t}$ Total accruals $ACC_{i,t}$ is earnings before extraordinary items and discontinued operations (COMPUSTAT item ibq) minus the operating cash flows (COMPUSTAT item oancfq) in quarter t, A_{t-4} is total assets (COMPUSTAT item atq) in quarter t-4, S_t is the change in sales (COMPUSTAT item saleq) from quarter t-4 to t and PPE_t is gross property plant and equipment (COMPUSTAT item ppegtq) in quarter t. Following Collins et al. (2014) we include fiscal quarter dummies $Q1_{i,t} - Q4_{i,t}$ to capture fiscal quarter effects and calculates changes in sales relatives to the same quarter previous year to avoid seasonality effects. The model is estimated cross-sectionally by year-industry (we define industry using 2-digit SIC code) with more than 15 observations using the entire sample of COMPUSTAT. Normal accruals are calculated as: $\frac{N\_ACC_{i,t}}{A_{i,t-4}} = \hat{\alpha}_0 + \hat{\alpha}_1(\frac{1}{A_{i,t-4}}) + \hat{\alpha}_2 Q_{1i,t} + \hat{\alpha}_3 Q_{2i,t} + \hat{\alpha}_4 Q_{3i,t} + \hat{\alpha}_5 Q_{4i,t} + \hat{\alpha}_6(\frac{\Delta S_{i,t} - \Delta AR_{i,t}}{A_{i,t-4}}) + \hat{\alpha}_7(\frac{PPEi,t}{A_{i,t-4}})$ Change in accounts receivables (COMPUSTAT item rectq) $AR_{i,t}$ from quarter t-4 to t is subtracted from change in sales as proposed by Dechow et al. (1995). Abnormal accruals $AB\_ACC_{i,t}$ are calculated as: $AB\_ACC_{i,t} = \frac{ACC_{i,t}}{A_{i,t-4}} - \frac{N\_ACC_{i,t}}{A_{i,t-4}}$	AB_ACC
Leverage	Long-term debt (COMPUSTAT item dlttq) divided by total assets (COMPUSTAT item atq).	LEV
Growth Prospect	Book to market ratio, book value of equity (COMPUSTAT item ceqq) divided by market value of equity (COMPUSTAT item prccq times COMPUSTAT item cshoq).	BTM
Firm Size	Natural logarithm of sales in quarter t. (COMPUSTAT item saleq).	$SIZE$
Flexibility in Real Activities Manipulation	Operating cycle measured in days calculated as: $[(AR_t + AR_{t-4})/S_t + (INV_t + INV_{t-4})/COGS_t] * 180$ Where AR_t are account receivables (COMPUSTAT item rectq) in quarter t,INV_t is total inventories (COMPUSTAT item invtq) in quarter t, S_t is sales (COMPUSTAT item saleq) in quarter t and $COGS_t$ is cost of goods sold (COMPUSTAT item cogsq) in quarter t.	$OPCYCLE$

(continue on next page)

APPENDIX C - (*continued*)

Construct	Proxy	Name
Capital Intensity	Is net PPE (COMPUSTAT item ppentq) in quarter t divided total assets (COMPUSTAT item atq) in quarter t.	$CAPINT$
Performance	Is Net income before extraordinary (COMPUSTAT item niq) items in quarter t divided by total assets (COMPUSTAT item atq) in quarter t.	ROA
Cash-Flow Volatility	Standard deviations of operating cash flows over the prior 20 quarters divided by average total assets (COMPUSTAT item atq) over the same period. Quarterly operating cash flows are calculated as the difference of annual net operating cash flows (COMPUSTAT item oancfy) in quarter t and t-1 divided total assets (COMPUSTAT item atq) in quarter t.	S_CFO
Earnings Persistency	Persistence of earnings, measured by coefficient α_1 from the following model: $$EPS_t = \alpha_0 + \alpha_1 EPS_{t-4} + \epsilon_t$$ Where EPS_t is basic earnings per share excluding extraordinary items (COMPUSTAT item epspxq) for quarter t. The model is estimated using a rolling window of 20 quarters with at least 15 non-missing quarterly EPS.	$PERS$
Earnings Predictability	Predictability of earnings in quarter t is measured by the standard deviation over 20 quarters of the residuals from the above model.	$PRED$
Analyst Following	Is the number of analyst (IBES Summary item numest) following the company in quarter t. For companies not covered by IBES AF is set equal to zero	AF
Institutional Ownership	Shares held by institutional investors as a percentage of total outstanding shares (Thomson Reuters 13F item instown_perc) in quarter t.	$INST$
Audit Quality	Is a dummy variable equal to one if the auditor (COMPUSTAT item au) is a BIG 4 , and zero otherwise.	$BIG4$
Managerial Ability	Managerial ability is the residual from the estimation of firm efficiency by industry. They build a continuous measure ranging between 0 and 1, where 1 is the highest managerial ability (see Demerjian et al. (2012)). http://faculty.washington.edu/smcvay/abilitydata.html	MA_SCORE
Manufacturing Firms	Dummy variable indicating if the firm belong to a manufacturing industry (2-digit SIC codes 20-39) and zero otherwise.	$MANUF$
Earnings Management Suspect Firms	Dummy variable equal to one if the firm is suspect to manage earnings in quarter t and zero otherwise. First, suspect is set equal to one if: (1) earnings before extraordinary items and discontinued operations (COMPUSTAT item ibq) over total assets (COMPUSTAT item atq) is between 0 & 0.002; (2) annual increase in basic earnings per share excluding extraordinary items (COMPUSTAT item epspxq) is between 0 & 0.02 (two cents); (3) actual value of EPS meet or beat analyst consensus EPS by no more than two cents. Second, suspect is set equal to zero if: (a) suspect is not equal to one and earnings before extraordinary items and discontinued operations (COMPUSTAT item ibq) over total assets (COMPUSTAT item atq) is greater (lower) than 0.05 (-0.05); (b) suspect is not equal to one and annual increase in basic earnings per share excluding extraordinary items (COMPUSTAT item epspxq) is greater (lower) than 0.05 (-0.05). (c) suspect is not equal to one and analyst EPS surprise (positive or negative) is greater than five cents.	$SUSPECT$
Consistent Target Beating Firms	Dummy variable equal to one if the firm meet/beat earnings targets in at least four previous consecutive quarters and zero otherwise.	$CONS\_BEAT$
Financial Constraints	We use Farre-Mensa and Ljungqvist (2016) probability of default measure.	PD

Figure 1: Changes in Analyst Coverage Breakdown

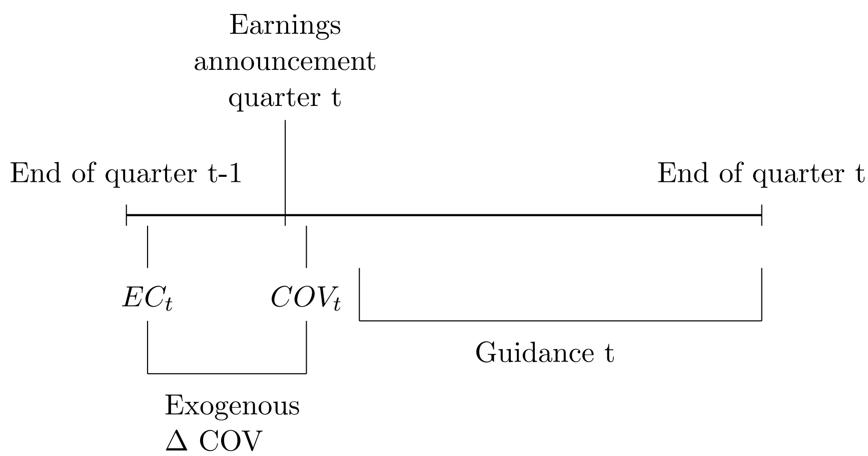

Table 1

Summary Statistics

Panel A: Compustat & I/B/E/S Coverage of U.S. Firms by Year

	Compusat	I/B/E/S Analyst Coverage[a]	I/B/E/S Guidance[b]		
Year	#Firms	#Firms	#Firms	%I/B/E/S	%Compustat
2003	10.943	4.814	1.613	33.51%	14.74%
2004	10.774	5.093	1.644	32.28%	15.26%
2005	10.853	5.318	1.391	26.16%	12.82%
2006	10.724	5.482	1.373	25.05%	12.80%
2007	10.507	5.621	1.143	20.33%	10.88%
2008	10.221	5.268	942	17.88%	9.22%
2009	10.149	5.096	774	15.19%	7.63%
2010	10.232	5.053	752	14.88%	7.35%
2011	10.616	5.038	765	15.18%	7.21%
2012	10.617	4.923	767	15.58%	7.22%
2013	10.193	5.149	761	14.78%	7.47%
2003-2013	**17.609**	**10.024**	**3.271**	**32.63%**	**18.58%**

Table 1 (*continued*)

Panel B: Descriptive Statistics

	Mean	Std. Dev.	1%	Q1	Median	Q3	99%
Dependent Variables [c]							
INC_REM	8.737	8.037	0.117	2.890	6.459	11.97	39.76
AB_PROD	4.160	6.538	-5.424	0.162	2.443	6.157	30.72
AB_DISEXP	4.521	4.574	-5.653	1.458	3.971	7.043	19.07
AB_RD[d]	0.189	0.664	-1.641	-0.015	0.052	0.400	2.488
AB_SGA[d]	2.313	4.206	-8.207	0.040	1.941	4.470	15.42
Control Variables[e]							
AB_ACC	0.016	0.119	-0.442	-0.021	-0.021	0.0479	0.476
AF	5.618	6.421	0	0	3	9	27
INST	0.553	0.330	0.000	0.242	0.634	0.831	1.119
SIZE	4.985	2.121	-0.037	3.555	5.019	6.424	9.527
LEV	0.166	0.179	0	0.003	0.128	0.260	0.799
BTM	0.596	0.949	-2.715	0.324	0.535	0.844	3.311
OPCYCLE	546.9	388.9	35.98	309.6	475.6	675.4	2,152
CAPINT	0.243	0.202	0.008	0.088	0.186	0.343	0.850
ROA	0.001	0.058	-0.254	-0.001	0.011	0.020	0.081
S_CFO	4.029	21.57	0.026	0.076	0.305	1.376	61.98
PERS	0.209	0.371	-0.654	-0.038	0.138	0.412	1.399
PRED	0.445	0.636	0.021	0.117	0.234	0.482	3.883

Table 1 (*continued*)

Panel C: Descriptive Statistics by GUIDE

	GUIDE= 0			GUIDE= 1		
	Mean	Median	S.D.	Mean	Median	S.D.
Dependent Variables						
INC_REM	8.811	6.542	8.119	8.498	6.188	7.762
AB_PROD	4.317	2.560	6.685	3.650	2.051	6.008
AB_DISEXP	4.425	3.844	4.625	4.834	4.308	4.389
AB_RD	0.182	0.038	0.672	0.213	0.112	0.636
AB_SGA	2.471	2.055	4.377	1.785	1.693	3.526
Control Variables						
AB_ACC	0.015	0.008	0.122	0.022	0.010	0.110
AF	4.478	2.000	5.917	9.301	8.000	6.601
INST	0.492	0.531	0.336	0.748	0.797	0.217
SIZE	4.746	4.728	2.200	5.759	5.701	1.617
LEV	0.169	0.125	0.185	0.158	0.138	0.157
BTM	0.606	0.550	1.052	0.565	0.495	0.485
OPCYCLE	553.6	473.4	407.8	525.1	480.5	319.0
CAPINT	0.256	0.202	0.208	0.201	0.145	0.175
ROA	-0.001	0.010	0.062	0.008	0.013	0.045
S_CFO	4.947	0.397	24.052	1.076	0.134	9.480
PERS	0.211	0.143	0.369	0.200	0.116	0.378
PRED	0.457	0.235	0.668	0.409	0.232	0.519

Table 1 (*continued*)

Panel D: Descriptive Statistics by SHOCK

	SHOCK= 0			SHOCK= 1		
	Mean	Median	S.D.	Mean	Median	S.D.
Dependent Variables						
INC_REM	9.007	6.694	8.189	7.702	5.519	7.332
AB_PROD	4.375	2.627	6.704	3.329	1.815	5.777
AB_DISEXP	4.567	4.058	4.691	4.344	3.641	4.088
AB_RD	0.194	0.056	0.678	0.170	0.038	0.591
AB_SGA	2.445	2.098	4.383	1.686	1.368	3.161
Control Variables						
AB_ACC	0.016	0.009	0.122	0.017	0.008	0.108
AF	4.071	2.000	5.388	11.567	11.000	6.602
INST	0.503	0.547	0.338	0.742	0.784	0.213
SIZE	4.610	4.629	2.067	6.429	6.382	1.655
LEV	0.158	0.111	0.181	0.198	0.177	0.168
BTM	0.619	0.568	1.045	0.506	0.431	0.393
OPCYCLE	556.584	484.697	393.641	509.733	435.824	367.606
CAPINT	0.235	0.182	0.194	0.277	0.200	0.226
ROA	-0.001	0.010	0.062	0.010	0.014	0.041
S_CFO	4.935	0.414	24.126	0.578	0.092	2.362
PERS	0.204	0.136	0.368	0.226	0.145	0.383
PRED	0.424	0.224	0.621	0.528	0.287	0.685

Table 1 (*continued*)

Panel E: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) INC_REM		**0.74**	**0.57**	**0.16**	**0.32**	**0.06**	**-0.09**	**-0.09**	**0.02**	0.00	**0.02**	**-0.13**	**-0.10**	**0.03**	**0.03**	0.01	**-0.05**
(2) AB_PROD	**0.83**		**-0.03**	**-0.07**	**0.06**	**-0.02**	**-0.13**	**-0.13**	**-0.02**	0.00	**0.05**	**-0.13**	**-0.06**	**-0.10**	**0.12**	0.00	-0.01
(3) AB_DISEXP	**0.53**	**-0.02**		**0.34**	**0.46**	**0.13**	**0.03**	**0.02**	**0.07**	**-0.03**	-0.01	**-0.09**	**-0.09**	**0.16**	**-0.10**	0.00	**-0.07**
(4) AB_RD	**0.12**	**-0.05**	**0.29**		**0.19**	**0.06**	**0.03**	**0.02**	0.01	**-0.03**	**-0.09**	**0.05**	**-0.09**	**0.10**	**-0.03**	**0.02**	**-0.05**
(5) AB_SG&A	**0.27**	**0.05**	**0.42**	**0.17**		0.00	**-0.13**	**-0.09**	**-0.21**	**-0.04**	**0.02**	-0.01	**-0.03**	0.00	**0.12**	0.00	**-0.11**
(6) AB_ACC	**0.03**	**-0.06**	**0.13**	**0.04**	**-0.03**		**0.02**	0.00	**-0.03**	**-0.07**	**-0.04**	**0.04**	**-0.08**	**0.20**	**0.02**	**0.03**	**-0.10**
(7) AF	**-0.09**	**-0.13**	**0.03**	0.01	**-0.13**	**0.03**		**0.73**	**0.68**	**0.19**	**-0.27**	**-0.07**	**-0.02**	**0.22**	**-0.57**	**0.05**	**0.18**
(8) INST	**-0.11**	**-0.13**	**0.02**	**0.00**	**-0.09**	0.01	**0.58**		**0.56**	**0.16**	**-0.14**	**-0.04**	**-0.07**	**0.20**	**-0.48**	**0.04**	**0.24**
(9) SIZE	**0.03**	-0.01	**0.08**	0.00	**-0.17**	-0.01	**0.62**	**0.54**		**0.36**	**-0.15**	**-0.19**	**0.09**	**0.24**	**-0.75**	**0.06**	**0.39**
(10) LEV	**-0.02**	**-0.01**	**-0.04**	-0.01	0.01	**-0.06**	**0.11**	**0.12**	**0.24**		**-0.11**	**-0.08**	**0.29**	**-0.11**	**-0.28**	**-0.03**	**0.23**
(11) BTM	0.00	-0.01	**0.02**	**-0.03**	**0.02**	**0.02**	**-0.11**	**-0.06**	**-0.09**	**-0.14**		**0.09**	**0.00**	**-0.32**	**0.12**	**-0.11**	**0.10**
(12) OPCYCLE	**-0.11**	**-0.08**	**-0.10**	0.00	**-0.02**	0.01	**-0.05**	**-0.06**	**-0.21**	**-0.07**	**0.09**		**-0.10**	**-0.06**	**0.05**	**-0.03**	**-0.02**
(13) CAPINT	**-0.13**	**-0.09**	**-0.10**	**-0.06**	-0.01	**-0.05**	**-0.01**	**-0.08**	**0.02**	**0.29**	0.01	**-0.17**		**-0.02**	**-0.04**	0.01	**0.11**
(14) ROA	0.00	**-0.07**	**0.13**	0.01	**-0.04**	**0.27**	**0.13**	**0.17**	**0.24**	**-0.07**	**0.03**	**-0.07**	**-0.03**		**-0.13**	**0.19**	**-0.13**
(15) S_CFO	**0.03**	**0.03**	-0.01	-0.01	**0.02**	**0.05**	**-0.15**	**-0.23**	**-0.29**	**-0.08**	**0.01**	**0.04**	**-0.05**	**-0.09**		**-0.03**	**-0.32**
(16) PERS	0.01	0.01	0.00	**0.02**	-0.01	**0.03**	**0.06**	**0.05**	**0.07**	**-0.03**	**-0.04**	-0.01	0.00	**0.08**	**-0.03**		**-0.21**
(17) PRED	**-0.03**	**-0.01**	**-0.03**	**-0.03**	**-0.04**	**-0.07**	**0.12**	**0.17**	**0.28**	**0.23**	**-0.03**	**-0.07**	**0.13**	**-0.07**	**-0.08**	**-0.16**	

Panel A: Summarizes the evolution of firms covered by Compustat and I/B/E/S by year

Panel B: Present descriptive statistics for the full sample. The sample consist of 32.841 firm-quarter observations for the period 2003-2013

Panel C: Present descriptive statistics by GUIDE. The sample of non-guiding firms ($GUIDE = 0$) consist of 25.080 firm quarters and the sample of guiding firms ($GUIDE = 1$) consist of 7.761 firm-quarters.

Panel D: Present descriptive statistics by SHOCK. The sample of non-shocked firms ($SHOCK = 0$) consist of 26.064 firm quarters and the sample of shocked firms ($SHOCK = 1$) consist of 6.777 firm-quarters

Panel E: Present the correlations between the variables.The table show Pearson correlation coefficients below the diagonal and Spearman coefficients above. Bold figures represent statistically significance at least at 10% level.

[a] At least one analyst making forecast on the company earnings per share in that year. [b] Firms issuing quarterly earnings per share guidance. The number of firms isuing guidance is greater if we consider other measures (i.e. Sales, Capex,EBITDA). [c] Dependent variables are multiplied by 100, their summary values represent percentage of total assets. [d] Estimated following Gunny (2010). [e] See APPENDIX-A for control variables definitions.Continuous variables are winsorized at the 1% and 99% levels.

Table 2
Real Activities Manipulations and Quarterly Earnings Guidance

VARIABLES	INC_REM	INC_REM	INC_REM	INC_REM
$GUIDE_t$	0.289**	0.345**	0.359**	0.374**
	(0.138)	(0.146)	(0.146)	(0.147)
$SHOCK_t$	-	0.182*	0.180*	0.198*
	-	(0.102)	(0.102)	(0.106)
$GUIDE * SHOCK_t$	-	-0.413**	-0.411**	-
	-	(0.161)	(0.161)	-
$GUIDE\_EARLY * SHOCK_t$	-	-	-	-0.231
	-	-	-	(0.563)
$GUIDE\_LATE * SHOCK_t$	-	-	-	-0.437***
	-	-	-	(0.166)
AB_ACC_{t-4}	-0.403	-0.365	-0.182	-0.183
	(0.339)	(0.337)	(0.357)	(0.357)
AF_{t-4}	0.033	0.034	0.031	0.031
	(0.023)	(0.023)	(0.023)	(0.023)
$INST_{t-4}$	-0.136	0.547	0.631	0.630
	(0.503)	(0.521)	(0.526)	(0.526))
$SIZE_{t-4}$	-1.418***	-0.947***	-0.964***	-0.964***
	(0.203)	(0.230)	(0.233)	(0.233)
LEV_{t-4}	-0.691	-0.999*	-0.983*	-0.983*
	(0.575)	(0.568)	(0.569)	(0.569)
BTM_{t-4}	-0.336***	-0.257***	-0.269***	-0.269***
	(0.093)	(0.087)	(0.089)	(0.089)
$OPCYCLE_{t-4}$	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
$CAPINT_{t-4}$	2.226*	1.596	1.667	1.663
	(1.159)	(1.151)	(1.153)	(1.153)
ROA_{t-4}	4.503***	3.341***	3.352***	3.349***
	(1.123)	(1.124)	(1.145)	(1.145)
S_CFO_{t-4}	0.001	0.003	0.002	0.002
	(0.007)	(0.007)	(0.007)	(0.007)
$PERS_{t-4}$	0.111	0.135	0.153	0.152
	(0.178)	(0.180)	(0.181)	(0.181)
$PRED_{t-4}$	-0.447***	-0.321**	-0.334**	-0.333**
	(0.160)	(0.160)	(0.161)	(0.161)
Constant	17.145***	14.604***	13.546***	13.546***
	(1.067)	(1.153)	(1.179)	(1.179)
Observations	32,841	32,841	32,841	32,841
Number of ID	2,585	2,585	2,585	2,585
Time F.E.	Not Included	Year	Quarter	Quarter
Firm F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm
Adjusted R^2	0.637	0.616	0.618	0.618

The estimated model is: $INC\_REM_{i,t} = \alpha + \beta_1 GUIDE_{i,t} + \beta_2 SHOCK_{i,t} + \beta_3 GUIDE_{i,t} SHOCK_{i,t} + CONTROLS + TimeFE + FirmFE + \epsilon_{i,t}$ (5). $GUIDE_t$ takes value 1 if the firm issue guidance in t and zero otherwise. $SHOCK_t$ takes value 1 if the firm suffer an exogenous decrease in analyst coverage in t and zero otherwise. $GUIDE\_EARLY_t$ takes value 1 if guidance is made before earnings announcement of previous quarter earnings and zero otherwise. $GUIDE\_LATE_t$ takes value 1 if guidance is made after earnings announcement of previous quarter earnings and zero otherwise. See APPENDIX-C for control variables definitions. The sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 3

Different Shock Size

Dependent Variable:	INC_REM					
EXO_DEC_t	$\geq 5\%$	$\geq 10\%$	$\geq 20\%$	$\geq 30\%$	$\geq 60\%$	$0\% - 60\%$
$GUIDE_t$	0.327**	0.312**	0.310**	0.290**	0.257*	0.359**
	(0.143)	(0.140)	(0.138)	(0.137)	(0.136)	(0.145)
$SHOCK_t$	0.102	0.092	0.285*	0.295	0.050	0.185*
	(0.104)	(0.118)	(0.152)	(0.193)	(0.325)	(0.101)
$GUIDE\_SHOCK_t$	-0.345**	-0.364*	-0.711***	-0.775**	0.077	-0.427***
	(0.174)	(0.186)	(0.248)	(0.332)	(0.764)	(0.162)
Observations	32,841	32,841	32,841	32,841	32,841	32,841
Number of ID	2,585	2,585	2,585	2,585	2,585	2,585
Control Variables	Included	Included	Included	Included	Included	Included
Time F.E.	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.618	0.618	0.618	0.618	0.617	0.618

EXO_DEC_t is the difference between the expected coverage for quarter t ($EC_{i,t}$), and the realized coverage after the announcement of previous quarter earnings ($COV_{i,t}$) divided by realized coverage ($COV_{i,t}$). The sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 4

Different Control Samples

Panel A: Estimation Results

Dependent Variable:	(1)	(2)	(3)
INC_REM_t	Guiding Firms	PSM	Placebo Shock
$GUIDE_t$	0.338**	0.257	0.251*
	(0.148)	(0.177)	(0.134)
$SHOCK_t$	0.144	-0.039	0.006
	(0.111)	(0.107)	(0.086)
$GUIDE\_SHOCK_t$	-0.357**	-0.349*	0.027
	(0.166)	(0.180)	(0.152)
Observations	20,630	12,458	32,841
Number of ID	1,341	1,607	2,585
Control Variables	Included	Included	Included
Time F.E.	Quarter	Quarter	Quarter
Firm F.E.	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm
Adjusted R^2	0.631	0.695	0.617

Column (1) present the results of estimating equation (5) using guiding firms in non-guiding quarters as a control sample. Column (2) present the results of estimating equation (5) using a propensity score matching methodology, we match firms in size, performance, leverage, book-to-market and analyst coverage before the shock, and requires firms to be in the same industry-quarter. Column (3) present the results of estimating equation (5) using a random generated shock replicating the proportion of shocked firms in the original sample. The full sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 4 (*continued*)

Panel B: Balance Properties Propensity Score Matching

Variable	Unmatched / Matched	Mean Treated	Mean Control	% bias	% Dec. bias	t-test t	t-test p>t	V(T)/V(C)
SIZE	U	6.181	4.113	102.5	90.4	96.7	0	0.76
	M	6.068	6.266	-9.8		-9.33	0	0.89
ROA	U	0.01	-0.006	28.4	91.5	24.4	0	0.24
	M	0.01	0.011	-2.4		-3.33	0.001	1.39
LEV	U	0.19443	0.156	21.2	65.4	21.32	0	0.91
	M	0.19493	0.208	-7.3		-5.77	0	0.97
AF	U	10.905	3.092	127.7	95.5	148.02	0	0.73
	M	10.171	9.821	5.7		3.95	0	0.93
BTM	U	0.505	0.664	-18.3	68.9	-15.36	0	0.14
	M	0.512	0.463	5.7		5.8	0	0.34

Sample	Ps R2	LR chi2	p > chi2	Mean bias	Med bias	B	R	% Conc.	% Bad
Unmatched	0.233	16036.42	0	45.9	21.2	136.7	1.31	29	29
Matched	0.007	223.8	0	4.6	5.7	19.4	0.8	14	14

Table 5

Different Monitoring

Dependent Variable: INC_REM				
Sample:	Low AF	High AF	No Big-Four	Big-Four
$GUIDE_t$	0.576**	0.120	1.185**	0.104
	(0.230)	(0.166)	(0.488)	(0.152)
$SHOCK_t$	0.551**	0.028	0.360	0.122
	(0.260)	(0.105)	(0.433)	(0.103)
$GUIDE\_SHOCK_t$	-1.040**	-0.225	-1.609**	-0.179
	(0.411)	(0.175)	(0.681)	(0.170)
Observations	18,408	14,433	8,159	21,602
Number of ID	1,927	1,195	855	1,768
Control Variables	Included	Included	Included	Included
Time F.E.	Quarter	Quarter	Quarter	Quarter
Firm F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm
Adjusted R^2	0.581	0.690	0.602	0.666

Low AF sample include firm-quarters with analyst coverage lower or equal to four. High AF sample include firm-quarters with analyst coverage greater than four. Non Big-Four sample include firm-quarters not audited by a Big-Four auditing firm. Big-Four sample include firm-quarters audited by a Big-Four auditing firm. The full sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 6

Different Likelihood to Manipulate Real Earnings Management

Dependent Variable: INC_REM

Sample:	Suspect Firms	Non-Suspect Firms	Consistent Beater	Non-Consistent Beater	Manufact. Industries	Non-Manufact. Industries	Fina. Constrained	Non-Fin. Constrained
$GUIDE_t$	1.217***	0.301*	1.572**	0.302**	0.427**	0.239	0.483**	0.241
	(0.464)	(0.154)	(0.624)	(0.150)	(0.176)	(0.250)	(0.211)	(0.179)
$SHOCK_t$	0.339	0.152	0.469	0.178*	0.135	0.227	-0.111	0.302**
	(0.513)	(0.104)	(0.537)	(0.104)	(0.111)	(0.195)	(0.167)	(0.120)
$GUIDE\_SHOCK_t$	-0.883	-0.333*	-1.276*	-0.330**	-0.474**	-0.323	-0.280	-0.453**
	(0.621)	(0.181)	(0.678)	(0.167)	(0.184)	(0.288)	(0.235)	(0.196)
Observations	3,194	29,097	1,725	31,116	20,775	12,066	14,186	18,655
Number of ID	1,327	2,542	345	2,551	1,497	1,088	2,100	2,083
Control Variables	Included	Included	Included	Included	Included	Included	Included	Included
Time F.E.	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.490	0.612	0.700	0.620	0.588	0.669	0.602	0.635

Suspect Firms sample include firm-quarters suspect of earnings management. Consistent Beater sample include firm-quarters meeting/beating earnings in four consecutive quarters Manufacturing Industries sample include firm-quarters with 2-digit SIC codes between 20 and 39. Financially Constrained sample include firm-quarters with a default probability greater or equal to 20%. See APPENDIX-C for variable definitions. The full sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 7

Different Managerial Ability

Dependent Variable: INC_REM		
Sample:	Low Ability Managers	High Ability Managers
$GUIDE_t$	0.436**	0.316
	(0.184)	(0.207)
$SHOCK_t$	0.065	0.234
	(0.148)	(0.143)
$GUIDE\_SHOCK_t$	-0.089	-0.636***
	(0.199)	(0.244)
Observations	9,475	23,366
Number of ID	738	2,305
Control Variables	Included	Included
Time F.E.	Quarter	Quarter
Firm F.E.	Yes	Yes
Cluster S.E.	Firm	Firm
Adjusted R^2	0.625	0.606

Low Ability Managers sample include firm-quarters with a MA_SCORE rank lower or equal to 0.6. High Ability Managers sample include firm-quarters with a MA_SCORE rank greater than 0.6. See APPENDIX-C for variable definitions. The full sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 8

Guidance Frequency & the Decision to Stop Guidance

Dependent Variable: INC_REM

VARIABLES	Low FREQ	Mid FREQ	High FREQ
$GUIDE_t$	0.437*	0.791***	-0.061
	(0.232)	(0.269)	(0.243)
$SHOCK_t$	0.310**	0.072	-0.110
	(0.132)	(0.218)	(0.215)
$GUIDE\_SHOCK_t$	-0.636*	-0.658**	-0.058
	(0.363)	(0.330)	(0.259)
$STOP\_INFO_t$	0.659	0.854	1.130
	(0.707)	(1.175)	(1.059)
$STOP\_STRATEGIC_t$	-0.971*	0.567	0.152
	(0.529)	(0.561)	(0.606)
Observations	22,005	5,005	5,831
Number of ID	2,058	648	498
Control Variables	Included	Included	Included
Time F.E.	Quarter	Quarter	Quarter
Firm F.E.	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm
Adjusted R^2	0.606	0.752	0.699

FREQ range from 1 to 10 indicating the deciles of the industry's guidance frequency distribution. Low FREQ sample includes firm-quarters within deciles 1 to 4 of FREQ. Mid FREQ sample includes firm-quarters within deciles 5 to 7 of FREQ. High FREQ sample includes firm-quarters within deciles 8 to 10 of FREQ. STOP_INFO is a dummy variable equal to one for firm-quarters after the decision to stop guidance if the last guidance was informative, and zero otherwise. STOP_STRATEGIC is a dummy variable equal to one for firm-quarters after the decision to stop guidance if the last guidance was strategic and zero otherwise. The full sample consist of 32.841 firm-quarter observations for the period 2003-2013. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * Indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Chapter 2

Conditional Conservatism and Management Earnings Forecasts

2.1 Introduction

We test the hypothesis that conditional conservatism and voluntary disclosure of management's private information are complementary mechanisms. Conditional conservatism in accounting stems from the asymmetric verifiability requirements that result in economic losses being recognized in a more complete and timelier manner than gains (Basu, 1997). LaFond and Watts (2008) argue that conditional conservatism allows other sources of information to flourish, by providing a hard benchmark that "makes it possible for alternative 'soft' sources to generate credible information on unverifiable gains" (LaFond and Watts, 2008, p. 452).[1] This idea that financial statements discipline other softer sources of information (including management-initiated disclosures) is not novel (see, e.g., Ball (2001); Watts (2006)), but has received limited empirical attention and, as noted in Ball et al. (2012), little is known about how firms credibly commit to different levels of disclosure of private information.

Theoretically, voluntary disclosure can play an informational role if there is a mechanism that allows managers to truthfully disclose their private information. Otherwise, unverifiable disclosures are uninformative in equilibrium (Crawford and Sobel, 1982). In this paper, we study if conditional conservatism acts as a hard benchmark that lends credibility to managerial good news disclosure, enabling it to 'flourish.' In particular, we focus on the links between firm commitment to conditional conservatism and management guidance behavior. If conservatism, by delaying (accelerating) the

[1] LaFond and Watts (2008) argue that in the presence of uncertainty conditional conservatism has an information role. First, conservatism acts as a governance mechanism that reduces managerial incentives and ability to manipulate accounting earnings. Second, conservative accounting provides a benchmark for current performance that enables other sources of information to produce credible information.

accounting *recognition* of good (bad) news, lends credibility to managerial *disclosure*, we expect that more conditionally conservative firms (a) disclose good news more frequently; and (b) third parties lend greater credibility to such firm-initiated disclosures.

Although no prior research directly tests our predictions, the existing literature offers theoretical support for them. For example, Guay and Verrecchia (2007) analytically demonstrate that firm commitment to a conditionally conservative reporting system, combined with voluntary disclosure of good news, leads to full disclosure, whereby all news about the firm are communicated to markets in a timely manner, lowering the discount applied by markets in the presence of uncertainty. A further link between conditional conservatism and good news disclosure that also lends support to the aforementioned predictions is explored in Bertomeu and Marinovic (2016). These authors model optimal disclosure via hard verifiable information and soft disclosures, and predict that hardness in financial statements and soft disclosure might be complementary.

Using a large sample of US publicly-listed firms for the period 1997-2014, we test if firm commitment to conditional conservatism (i.e. an ex-ante managerial choice that prevents aggressive accounting) triggers the disclosure of good news and lends credibility to management forecast disclosures. In line with prior research we consider conservatism as “being exogenous and predetermined for the current generation of managers” (García Lara et al., 2016a, p. 225). We measure commitment to conditional conservatism using the decile ranking of the average past three- and past five-years of the Khan and Watts (2009) measure. This measure takes into account how firm-specific characteristics affect conditional conservatism over time. It also captures the properties of accounting conservatism that are of interest to our study: the timeliness of losses and the differential timeliness of good and bad news recognition.

First, we use Khan and Watts (2009) proxy to examine the association between conditional conservatism and management forecasts. Then, we assess the effects of conservatism over the credibility of management forecasts. Credibility is a subjective attribute of disclosure, related to investors’ appraisal of the believability of a given disclosure (Mercer, 2004). We follow prior work and study management forecasting behavior and the market reaction to those forecasts, to provide evidence on whether forecast credibility increases in the commitment to conditional conservatism.

We report the following key findings. We find that conditional conservatism is positively (negatively) associated with higher frequency of good (bad) news management earnings forecasts, and that this association is stronger for good news management forecasts when future stock returns are positive. This finding is consistent with more conditional conservative firms issuing more guidance when future good news is anticipated.

Next, we focus on analysts' and market reactions to forecasts. This permits assessing the credibility of management-initiated earnings forecasts. Prior literature suggests that analysts' and market reactions to management forecasts depend on (1) the magnitude of the news contained in the forecast and (2) the extent to which the forecast is perceived as credible (Jennings, 1984, 1987; Ng et al., 2013). Based on prior literature, Mercer (2004) proposes a framework to assess disclosure credibility. She argues that there are four main determinants of disclosure credibility: (1) situational incentives; (2) management credibility; (3) external and internal assurance, and (4) disclosure characteristics. Controlling for the magnitude of the news as well as for the determinants of credibility, we find that after a management forecast, analysts' revisions are greater and lead to larger reductions in forecast errors for more conditionally conservative firms.[2] Further, analysts' estimates dispersion after a management forecast is lower for more conditionally conservative firms. Overall, we interpret this evidence as analysts assessing management forecasts as being more credible when issued by conditionally conservative firms. We also find stronger markets reaction (i.e. larger cumulative abnormal returns) to good news management forecasts issued by more conditionally conservative firms, but not to bad news forecasts. This evidence suggests consistency in the evaluation of management forecasts credibility, and provides further support to our predictions.

Despite our view that firm-level conservatism is predetermined for current managers, we cannot completely dismiss endogeneity concerns (i.e. potential correlated omitted variables). To alleviate these concerns we include in our models year- and industry-fixed effects to control for economic trends and time invariant firm-specific factors that might be confounding variables of conditional conservatism in explaining management forecasting behavior. We also control for corporate governance quality, given the evidence in prior work that both conditional conservatism and voluntary disclosure are influenced by the quality of corporate governance (Eng and Mak, 2003; Ahmed and Duellman, 2007).

Furthermore, to better establish a causal link we conduct two additional tests. First, we exploit the implementation of the Statement of Financial Accounting Standards No. 142, *Goodwill and Other Intangible Assets* (FASB 2001, hereafter "SFAS 142") as a plausible exogenous shock to conditional conservatism. Cedergren et al. (2015) argue that SFAS 142 forces a greater degree of conditional conservatism into the reporting system relative to the previous reporting regime, because it requires annual impairment testing and imposes stricter tests.[3] Consistent with the idea that SFAS 142 increased conditional conservatism, Li et al. (2011b) document an increase in the frequency of goodwill

[2] We also control for the possibility that analysts may systematically issue biased forecasts for more conditionally conservative firms (e.g., Helbok and Walker (2004))

[3] The previous standard was the Statement of Financial Accounting Standards No. 121, *Accounting for the Impairment of Long-Lived Assets and for Long-Lived Assets to be Disposed Of* (hereafter "SFAS 121").

impairments after SFAS 142. We find that this plausible exogenous increase in conditional conservatism leads to an increase in good news management earnings forecasts. Second, we follow Lins et al. (2017) and use their shocks to overall credibility to assess whether management forecasts issued by more conservative firms elicit stronger market reactions during unexpectedly "low trust" periods. Our evidence indicates that conditionally conservative firms are more resistant to credibility shocks and that the beneficial consequences of conservatism over managerial forecasting extend to crisis of trust periods.

Our paper makes a number of contributions to the literature. First, we contribute to the literature investigating conditional conservatism and voluntary disclosure, by providing novel evidence consistent with conditional conservatism acting as a mechanism that disciplines disclosure and allows other 'softer' sources of information to thrive. We document a complementary relation between conditionally conservative reporting and voluntary managerial disclosure of good news information. This is consistent and adds to the prior line of research that studies the beneficial consequences of conservatism in accounting (e.g., LaFond and Watts (2008)). There is no prior work directly examining whether conditional conservatism acts as a mechanism that enables good news disclosure, enhancing the credibility of management forecasts. However, the work of Hui et al. (2009) and D'Augusta and DeAngelis (2017) are closely associated. Hui et al. (2009) study the relation between unconditional conservatism and management forecasts, taking a different theoretical and empirical stance. They argue that conservatism reduces information asymmetries between managers and shareholders, and thus, serves as a *substitute* to management forecasts. Whilst this would hold for bad news disclosure, where timely recognition of losses could plausibly substitute for its timely disclosure, we argue that it cannot hold for good news, as conservatism delays the recognition of good news, and thus, cannot act as a substitute for timely good news disclosure. A second fundamental difference with Hui et al. (2009) is that they focus on unconditional conservatism (i.e. news independent). It is unlikely that this type of conservatism bears a contracting/information role (see, e.g., Beaver and Ryan (2005); Ball and Shivakumar (2005)). Also relevant to our study is the work of D'Augusta and DeAngelis (2017), which reports a negative association between conditional conservatism and tone management in the Management Discussion and Analysis (MD&A) section of 10K filings. This is consistent with conservatism acting as a disciplining mechanism of softer sources of disclosure.

A further contribution of our study is to provide empirical evidence in favor of the arguments in LaFond and Watts (2008) and Guay and Verrecchia (2007) that firm commitment to a conditionally conservative reporting system enhances the credibility of good news disclosure, potentially leading to full disclosure. Our results provide novel insights on the causal links between conditional conservatism and voluntary disclosure, by showing that a plausible exogenous shock to conditional conservatism increases the frequency of good news management earnings forecasts. This evidence is of relevance in light of the decade-long debate of FASB, IASB and other regulatory bodies on whether conservatism is a desirable property of accounting information that should be included into accounting conceptual frameworks. Our results are consistent with beneficial consequences of conservatism over voluntary disclosure.

The remainder of the paper is organized as follows. Section 2 revises prior literature and develops our main hypotheses. Section 3 describes our research design. Sections 4 and 5 discuss the sample and empirical results, and Section 6 presents additional analyses. Finally, Section 7 summarizes and concludes our study.

2.2 Conditional Conservatism and Voluntary Disclosure

The existence of asymmetric verifiability requirements for the recognition of economic gains and losses in financial statements means that economic losses (bad news) and economic gains (good news) are treated asymmetrically, particularly when the news is hard-to-verify. This leads to differential timeliness and persistence of good *versus* bad news, with bad news being recognized in a timelier and more complete manner than good news (Basu, 1997). The extant prior literature refers to this form of conservatism as conditional conservatism.[4]

In this section, we outline our main hypothesis that conditional conservatism disciplines managerial voluntary disclosure, influencing its timing and credibility. We start by reviewing the general literature that establishes that financial reporting quality acts a as mechanism through which managers can commit to truthful disclosure of private information.

2.2.1 Financial Reporting and Voluntary Disclosure as Complements

At the core of financial reporting is the concept of decision usefulness. The *International Accounting Standards Board*, in its Conceptual Framework (developed within the IASB-FASB joint project), notes that financial information is capable of making a difference in decisions "if it has predictive value, confirmatory value or both" (IASB, 2010, QC7). Confirmatory value means that financial information can provide feedback about (confirms or changes) previous evaluations.[5] While largely unexplored

[4]See Beaver and Ryan (2005) for an explanation of the difference between conditional and unconditional conservatism. Ball and Shivakumar (2005) argue that conditional conservatism has contracting value while unconditional conservatism only introduces a bias into reported earnings and reduces the scope for conditional conservatism.

[5]As noted in the conceptual framework, predictive and confirmatory value are interrelated, and information with predictive value often also has confirmatory value.

by empirical research, the confirmatory role of financial accounting is key to understand the relation between financial statements and other information sources (Cascino et al., 2017). For example, current reported revenue can be used as the basis for predicting future revenues, but importantly, it can also be used to compare it with revenue predictions for the current year that were made in past years using management forecasts as well as other industry- and market-wide information sources. Such comparisons, if unfavorable, would lead to corrections in the processes used by third parties in considering the information disclosed by the firm.

This confirmatory role of accounting implies that high quality financial reporting disciplines managerial voluntary disclosure both *ex-ante* and *ex-post*. Reported current period figures (earnings, revenues, cash flows, etc.) are observed by third parties, who can then detect deviations with respect to management forecasts issued in the past and assess the accuracy of prior voluntary disclosure. Boards, analysts and other interested parties can then question management on detected deviations *ex-post*. In turn, managers, aware that their forecasts will come under such scrutiny will make more truthful and informative disclosures *ex-ante*.

The above argumentation implies that the disciplining role over disclosure is increasing in the extent to which the accounting regime imposes that actual outcomes are accurately reported and lowers the opportunities to misreport current performance. Ball et al. (2012) provide evidence consistent with this claim. They build on Crawford and Sobel (1982) and argue that voluntary disclosure of information privately known to the firm can only play an informational role if there is a mechanism that allows managers to credibly commit to truthful disclosure. Ball et al. (2012) argue that a primary role of financial reporting is to supply information to use in efficient contracting and in particular, they propose that firms can make different commitments to truthful disclosure by choosing different levels of audit of financial outcomes, as measured by audit fees. They show that commitment to higher audit verification levels is associated with better quality disclosure, as measured by the frequency, specificity, accuracy and timeliness of management earnings forecasts.

The underlying idea that financial statements discipline disclosure appears in Ball (2001), Watts (2006) or LaFond and Watts (2008), who argue that financial reports based on independent verifiable outcomes provide investors with a hard benchmark against which to compare the credibility of other sources of information. Similarly, a number of analytical papers develop models in line with the hypothesis that mandatory reporting complements voluntary disclosure, or more generally, that 'hard' verifiable information and 'soft' disclosure have a complementary relationship (Gigler and Hemmer, 1998; Bertomeu and Marinovic, 2016). However, little empirical research to date has explored the mechanisms that managers can use to credibly commit to truthful disclosure of private information.

Exceptions include the work of Ball et al. (2012) and Beniluz (2005).[6] Both papers find evidence consistent with the view that accounting disciplines disclosure. In particular, Beniluz (2005) finds a negative relation between accounting quality, as measured using earnings management proxies, and the optimistic biases in both analysts and management earnings forecasts.

Finally, albeit not directly addressing this issue, a number of recent papers also report evidence of a positive association between accounting quality as measured by earnings quality and the incidence, frequency, and accuracy of voluntary disclosure (Lennox and Park, 2006; Francis et al., 2008; Gong et al., 2009), which is suggestive of reporting and disclosure acting as complements.

2.2.2 Conditional Conservatism and the Timing and Credibility of Managerial Voluntary Disclosure

In the absence of mechanisms that permit commitment to truthful disclosure, managers are expected to act strategically and use their private information for their own interests. This would lead to the prediction that voluntary disclosure focuses on news that emphasize positive aspects and affect stock prices favorably, while de-emphasizing negative news (Dye, 1985; Verrecchia, 1983).

Against this backdrop, we argue that conditional conservatism is an efficient mechanism that directly disciplines managerial disclosure. Conservatism imposes lower (higher) verification standards for the recognition of losses (gains). This results in the recognition of losses that managers would be unwilling to report otherwise. Conditional conservatism thereby reassures outside investors that unverifiable gains will not be overemphasized and that losses will not be under-reported, providing a 'hard' benchmark for current earnings.[7] Indeed, by imposing timely and complete recognition of bad news, third parties interested in the firm can directly assess the truthfulness of past management forecasts of current figures by comparing them with realized outcomes. If managers have been optimistic in their disclosures, conditional conservatism accelerates the discovery of poor quality disclosure, improving monitoring *ex-post*, i.e., it permits a wide range of financial statements users, from boards of directors to lenders or analysts, to detect and question managers on deviations between forecasts

[6] Some recent findings suggests that certain features of mandatory reporting and disclosure may be substitutes of voluntary disclosure. For example, Guay et al. (2016) argues and shows that greater complexity in mandatory disclosure (as measured by information readability) is associated with greater voluntary disclosure.

[7] To illustrate, consider the case of a pharmaceutical firm. If a medication is discovered to have side effects, the news would be recognized if it is bad (i.e., the treatment cures headaches but causes liver failure) by writing off any associated R&D assets and recognizing a provision for the firm best estimate of its expected future payments to those affected. That is, bad news is recognized in a timely and complete manner. However, if the news is good (i.e., the treatment cures headaches and also, acne), its recognition would be delayed until the increased sales and cash flows accrue to the firm. It would then be up to the firm to voluntarily disclose its best estimate of the expected value of this good news. In both scenarios, firms' commitment to conditional conservatism would reassure outside investors that good news are not overemphasized and that bad news are not under-reported.

and realizations. Recurrent deviations could, in the best case scenario, be interpreted as a sign of low managerial ability in forecasting, and in the worst case scenario, of managerial deceit. Knowing that conservatism negates the possibility of delaying the recognition of losses, and therefore, that optimistic forecasts will come under scrutiny in the short-term, means that conditional conservatism also deters managers from issuing untruthful disclosure *ex-ante*, as any unwarranted optimism unravels immediately: as soon as the outcomes realize.

Hence, conditional conservatism enhances the confirmatory role of accounting directly, because of its disciplining *ex-ante* and *ex-post* roles. In addition, conditional conservatism is predicted to enable disclosure and enhance its credibility indirectly at least through two channels.

First, conditional conservatism lowers managerial ability to misreport current performance. As noted above, the extent to which managers are able to misreport lowers the disciplining value of accounting. Watts (2003) and LaFond and Watts (2008) argue that managers have incentives to overemphasize unverifiable gains but tend to be unwilling to report on unverifiable losses. Conditional conservatism, by imposing lower verification standards for the recognition of losses relative to gains, acts as a governance mechanism that reduces managerial incentives and ability to manipulate earnings. García Lara et al. (2016b) study the links between earnings management and conditional conservatism and provide empirical support for this claim, while a number of studies provide evidence indicating that more conditionally conservative firms provide more accurate and reliable information. Particularly, conservatism is associated with improvements in the firm information environment, as indicated by lower cost of equity (García Lara et al., 2011), lower cost of debt and better assessment of default risk for lenders (Ahmed et al., 2002; Wittenberg-Moerman, 2008), and decreases in information asymmetry (Francis et al., 2013; Kim et al., 2013). Conservatism is also associated with better corporate governance (Beekes et al., 2004; Ahmed and Duellman, 2007). Overall, this body of research shows that conditional conservatism acts as a governance mechanism that improves contracting and lowers agency costs.

Second, conditional conservatism indirectly influences disclosure through its consequences over managerial decision-making. Prior literature indicates that conditional conservatism is useful to monitor and discipline managers, as it improves investment efficiency (Francis and Martin, 2010) and facilitates firm access to financing sources (Bhattacharya et al., 2003; Zhang, 2008). Conservatism has also been shown to lower stock price crash risk (Kim and Zhang, 2016), to improve the alignment of managerial decisions-making with shareholders' incentives (Louis et al., 2012), and to lead to higher SEO announcement returns due to lower financing costs in SEOs (Kim et al., 2013). Thus, conditional conservatism is expected to affect the underlying distribution of economic gains and losses (good and bad news), through better decision-making.

There is no prior empirical work directly studying our predictions. D'Augusta and DeAngelis (2017) provide empirical evidence suggesting that conditional conservatism lessens tone management in the MD&A section of the 10K filings of industrial companies, consistent with a disciplining role of conditional conservatism. Also related is the work of Hui et al. (2009), who study the links between conservatism and management forecasts, but focusing on unconditional conservatism, a news independent type of conservatism (Beaver and Ryan, 2005; Ball and Shivakumar, 2005).[8] This choice leads them to predict and report evidence that unconditional conservatism serves as a *substitute* to management forecasts. Whilst this may hold partially for realized bad news disclosure, where timely recognition of losses could substitute for timely disclosure, it does not hold for forward-looking disclosure of bad news or for good news disclosure, as conservatism delays the recognition of good news, and thus, cannot act as a substitute for timely good news disclosure. In agreement with this view, Jaggi et al. (2014) argue that Hui et al. (2009) results do not consider the heterogeneity in management forecasts, questioning the links between unconditional conservatism and management forecasts.[9] Perhaps closer to our argumentation is the theoretical work of Guay and Verrecchia (2007), who argue that in the presence of uncertainty, markets apply a discount to firm value because managers have incentives to act strategically (i.e. withhold bad news and disclose good news) when there is no mandatory disclosure requirements. They show that commitment to timely recognition of bad news, together with voluntary disclosure of good news results in full disclosure. Full disclosure implies that all news concerning firm value are more timely communicated to markets (i.e. no information is withheld), reducing the discount that markets apply in the presence of uncertainty. The theoretical model by Guay and Verrecchia (2007) suggests a complementary relationship between conditional conservatism and voluntary disclosure in communicating firm information.

2.2.3 Main Predictions

Given the above discussion, we formulate two empirical predictions. First, if conditionally conservative reports asymmetrically recognize unrealized gains and losses, with bad news being recognized in a more timely and complete manner, we expect that managers of more conditionally conservative firms will voluntarily issue more (less) good (bad) news information. Conditional conservatism imposes delayed

[8] They use the bias component of the book-to-market ratio as in Beaver and Ryan (2000), the negative accruals proxy of Givoly and Hayn (2000) and the C-score of Penman and Zhang (2002).

[9] Also related is the study of Li (2008), who argues that managers incentives to meet or beat analysts' forecasts lead them to issue more voluntary disclosure to inform analyst about the downward bias in earnings caused by unconditional conservatism, and induce a downward revision of analysts' forecasts. While Sun and Xu (2012) claim that management failure to fully incorporate historical accounting conservatism effects on realized earnings results in optimistically biased management forecasts.

good news recognition, i.e., often times, good news are not recognized until their associated cash flows are realized. This means that, by construction, conditionally conservative firms are unlikely to have (internally known) unrealized bad news they need to disclose to markets, as bad news are recognized in the firm financial statements more timely. In contrast, if the firm has (internally known) unrealized gains, the constraints imposed by conditional conservatism to the recognition of gains imply that the only way to communicate the good news to the market is thorough disclosure. Accordingly, our first hypothesis is:

> **H1:** *Conditional conservatism is positively (negatively) associated with managerial voluntary disclosure of good (bad) news information.*

Although this prediction might seem naïve, there are several reasons why is not obvious that more conditional conservative firms will disclose more good news information. First, committing to timely and complete recognition of bad news does not mean that firms will 'fabricate' future good news by overestimating the amount of recognized bad news. Against the common misconception that conditional conservatism is an income decreasing form of earnings management, García Lara et al. (2016b) find evidence consistent with conditional conservatism limiting downward accruals manipulation. Second, conditional conservatism does not eliminate incentives to meet-or-beat earnings (MBE) benchmarks, and sufficiently high MBE incentives may lead to more bad news disclosure (Konrad, 2018). Finally, it is not clear that debt-contracting incentives associated with conservatism will lead to more good news disclosures, given that bondholders might have more direct mechanisms to obtain firm information.

Our second empirical prediction is related with the effects of conservatism on disclosure credibility. Prior literature defines disclosure credibility as "investors' perceptions of the believability of a particular disclosure" (Mercer, 2004, p.186). Building on the previously reviewed literature that indicates that hardness in financial reporting lends credibility to softer sources of information, we predict that firm commitment to more conditional conservative reporting acts as a disciplining mechanism that lends credibility to managerial disclosure, enabling it to 'flourish,' and particularly, to good news disclosure, which, *ceteris paribus* would be subject to lower credibility, given the aforementioned managerial incentives to disclose strategically. Stated in the alternative form our second hypothesis is as follows:

> **H2:** *Conditional conservatism is associated with greater credibility of managerial voluntary disclosure of good and bad news information.*

2.3 Research Design

To test our predictions we use a proxy for commitment to conditional conservatism based on the measure of Khan and Watts (2009).[10] Starting from the Basu (1997) model:

$$X_i = \beta_1 + \beta_2 D_i + \beta_3 R_i + \beta_4 D_i R_i + e_i \tag{2.1}$$

Where the dependent variable, X_i, is earnings scaled by lagged price, R_i are annual stock returns, and D_i is a dummy variable equal to one if returns are negative and zero otherwise. Khan and Watts (2009) specify the Basu (1997) asymmetric earnings timeliness coefficients (β_3 and β_4) as a linear function of firm size, market to book and leverage:[11]

$$G\_SCORE \equiv \beta_3 = \mu_1 + \mu_2 Size_i + \mu_3 MtoB_i + \mu_4 LEV_i \tag{2.2}$$

$$C\_SCORE \equiv \beta_4 = \lambda_1 + \lambda_2 Size_i + \lambda_3 MtoB_i + \lambda_4 LEV_i \tag{2.3}$$

G_SCORE is a firm-year estimation of the timeliness to good news, and C_SCORE is a firm-year estimation of the incremental timeliness to bad news. The sum of both coefficients measures the total timeliness to bad news. Estimators of μ's and λ's are constant across firms but vary over time, therefore to obtain a firm-year measure of conditional conservatism Khan and Watts (2009) substitute equations (2) and (3) into regression model (1) to obtain the annual cross-sectional regression model used to estimate C_SCORE and G_SCORE:

$$\begin{aligned} X_i =& \beta_1 + \beta_2 D_i + R_i(\mu_1 + \mu_2 Size_i + \mu_3 MtoB_i + \mu_4 LEV_i) + D_i R_i(\lambda_1 + \\ & \lambda_2 Size_i + \lambda_3 MtoB_i + \lambda_4 LEV_i) + (\delta_1 Size_i + \delta_2 MtoB_i + \delta_3 LEV_i + \\ & \delta_4 D_i Size_i + \delta_5 D_i MtoB_i + \delta_6 D_i LEV_i) + \epsilon_i \end{aligned} \tag{2.4}$$

We take the three-year average of C_SCORE (i.e. incremental timeliness to bad news) and define our proxy for conditional conservatism as the annual decile of this average. We denote this measure as CO_RANK. Taking the three-year average helps us to better capture firm commitment to conditionally conservative financial reporting.[12]

As in García Lara et al. (2016a) we consider conservatism (i.e. an ex-ante commitment that

[10] While there are some concerns about the validity of Basu's (1997) derived measures of conditional conservatism (Patatoukas and Thomas, 2015), prior research (Ettredge et al., 2012; Jayaraman, 2012; Ball et al., 2013a,b) documents that Khan and Watts (2009) provides a valid measure of conditional conservatism.

[11] Prior literature shows that conservatism changes with these variables (e.g., LaFond and Watts (2008)).

[12] Taking the average and the decile rank of the average helps to mitigate measurement errors and nonlinearity concerns, facilitating the interpretation of our results.

prevents aggressive accounting) to be predetermined for current managers. In line with this view, reporting conservatism is expected to be stable over time Givoly et al. (2007), and prior literature show that conservatism measures are fairly stable at the firm level (Khan and Watts, 2009; Callen et al., 2010). Appendix A provides details on the estimation of C_SCORE and G_SCORE and validates our proxy of conditional conservatism.[13]

2.3.1 Conditional Conservatism and Management Forecast Frequency

Under H1, we hypothesize that conditional conservatism is associated with the frequency of good and bad news disclosure. To test this prediction we use the following simple model:

$$MF_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t \tag{2.5}$$

where, MF_t is a proxy for the frequency of good and bad news management forecast frequency. CO_RANK is our proxy of firm commitment to conditional conservatism as defined above. Model (5) incorporates industry- and year- fixed effects. Standard errors are clustered at the firm level.

Management forecast frequency is measured by $GUIDE$ and MF_REG. $GUIDE$ is a dummy variable equal to one if the firm issues an earnings per share (EPS) management forecast in a particular quarter and zero otherwise. Following Cheng et al. (2007b), we consider initial quarterly forecast of the next quarter's earnings issued within a window of (-90, 45) days, where day 0 is the fiscal quarter-end date.[14] MF_REG is a variable indicating the number of quarters in which the firm issues an EPS management forecast over the last four quarters.

To test H1, we divide our measures depending on whether they represent good or bad news disclosure. $GUIDE\_GN$ ($GUIDE\_BN$) disclosure is measured by a dummy variable equal to one if the EPS management forecast is greater (lower) than the mean analysts' consensus EPS estimate at the management forecast date and zero otherwise. MF_REG_GN (MF_REG_BN) indicates the number of quarters in which the firm issues a good (bad) news forecast over the last four quarters. Under H1, we expect β_1 in model (5) to be positive and significant for good news disclosures. In contrast, if timely recognition of losses acts as substitute for timely disclosure of losses, we expect a negative β_1 for bad news disclosures. A positive (negative) β_1 for good (bad) news disclosure implies that conditional conservatism acts as a complement for timely voluntary disclosure of good news and a substitute for timely disclosure of losses.

[13]Our results are robust to using also the five-year average, and total timeliness of loss recognition (C_SCORE + G_SCORE) as our proxy for conditional conservatism.

[14]In untabulated sensitivity analyses, we exclude forecasts made after fiscal quarter end (i.e. earnings pre-announcements), and our findings remain qualitatively similar.

We follow prior literature to control for other determinants of management forecast frequency. We control for firm size ($SIZE$) as the costs of voluntary disclosure decrease as firms' size increase (Lang and Lundholm, 1993; Kasznik and Lev, 1995; Baginski and Hassell, 1997); book-to-market (BTM) to take into account the effects of growth opportunities on firm's voluntary disclosure behavior (Bamber and Cheon, 1998); return on assets (ROA) to control for earnings performance effects on disclosure (Miller, 2002); number of analyst following (AF) and institutional ownership ($INST$) to proxy for the demand for firm forward-looking information, a positive association is expected (Ajinkya et al., 2005; Healy and Palepu, 2001; Hirst et al., 2008); analysts forecast dispersion (DIS) is expected to be negatively associated with management earnings forecasts because managers might perceive that earnings are harder to predict (Healy and Palepu, 2001; Ajinkya et al., 2005); earnings volatility (S_EARN), cash-flow volatility (S_CFO), and stock return volatility (RET_VOL) to proxy for uncertainty and the difficulty in predicting earnings (Waymire, 1985; Healy and Palepu, 2001); litigation risks (LIT) because firms in high litigation industries are more likely to issue guidance to avoid potential litigation caused by withholding information (Skinner, 1994, 1997; Rogers and Stocken, 2005). We also control for bid-ask spread (BID_ASK) as a proxy for information asymmetry, a positive association is expected. See Appendix B for variables definitions.

In addition to $SIZE$ and BTM we also control for leverage (LEV), these three variables are used to calculate our measure of conditional conservatism. Including these variables as controls alleviates concerns that our measure of conservatism captures the effect of these variables.

2.3.2 Conditional Conservatism and the Credibility of Management Forecasts

Under H2, we hypothesize that conditional conservatism lends credibility to management earnings forecasts. To test this prediction we use the following model:

$$\begin{aligned} Y_t = &\beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * N\_SIZE + \beta_3 * N\_SIZE * CO\_RANK_{t-n} \\ &+ \gamma * Controls_t + \epsilon_t \end{aligned} \tag{2.6}$$

where, Y_t is a proxy for management forecast credibility. Model (6) incorporates industry- and year- fixed effects. Standard errors are clustered at the firm level.

We define management forecast credibility following prior work (Jennings, 1987; Mercer, 2004; Hutton et al., 2003), and measure it using the reaction to management forecasts. To the extent that conservatism lends credibility to management voluntary disclosure, allowing softer sources of information on difficult-to-verify good news to flourish, we expect conditionally conservative firms will experience a larger analysts' and market reaction in response to management forecasts. However, analysts' and market reactions are a function of both the news embedded in the forecast, and its credibility (Jennings, 1987; Ng et al., 2013). In our model, the magnitude of forecasts news is captured by N_SIZE, which is the absolute value of the difference between management earnings forecasts (midpoint for range forecasts) and the most recent mean consensus analyst forecast. While the interaction term $N\_SIZE * CO\_RANK$ isolates the credibility portion of the reaction to management forecasts.

Mercer (2004) literature review proposes a framework to evaluate disclosure credibility, based on four factors: (1) *Situational Incentives*, investors are less likely to believe managerial disclosure when managers have incentives to be untruthful. Prior work suggests that investors react to management forecasts as if they understand situational incentives. For example, bad news are expected to be more credible because managers have incentives to be optimistic in their disclosures (McNichols, 1989). Accordingly, several studies find that bad news management forecasts lead to larger analyst forecast revisions and stock price reactions relative to good news forecasts (Williams, 1996; Skinner, 1994; Soffer et al., 2000; Hutton et al., 2003; Ng et al., 2013). Analysts' and market responses are also consistent with situational incentives related to financial distress, litigation risk, insider trading, and competitive pressures. [15] (2) *Management Credibility*, investors are less likely to believe managers with bad reputations. Existing empirical evidence suggests that markets and investors response to management forecasts is larger when managers develop a reputation of issuing accurate forecasts (Williams, 1996; Ng et al., 2013). (3) *External and Internal Assurance*, external (e.g. auditors) and internal (e.g. board of directors) assurance can increase disclosure credibility. Prior literature find evidence consistent with governance mechanisms affecting disclosure credibility (Ajinkya et al., 2005; Karamanou and Vafeas, 2005). (4) *Disclosure Characteristics*, various aspects of the disclosure are likely to affect its credibility. These features include the disclosure's precision, venue, horizon, supporting information and inherent plausibility. Prior literature finds that more precise, timely, plausible management forecasts and those accompanied by supporting information are perceived as more credible (Mercer, 2004; Hirst et al., 2008).

We follow the framework in Mercer (2004) and control for several factors associated with disclosure credibility. We control for financial distress (FD), litigation risk (LIT), insider transactions ($INSIDE$) and industry concentration (HHI) to account for *situational incentives*. We control for

[15] Prior work shows that financially distressed firms have greater incentives to issue misleading forecasts because the benefits (costs) of inaccuracy are higher (lower) (Koch, 2002); also, that firms facing greater litigation risk are more likely to issue less (more) optimistic (pessimistic) forecasts (Rogers and Stocken, 2005), and managers have more incentives to mislead when trading opportunistically on their own stock (e.g. insider acquisitions after a bad news forecasts) (Rogers and Stocken, 2005). Finally, managers of firms in more concentrated industries have greater incentives to mislead (i.e. issue overly pessimistic forecasts) to discourage entry (Rogers and Stocken, 2005).

prior management forecast accuracy ($ACCURACY$) as a proxy for *management credibility.* To account for *external and internal assurance* effects we control for institutional ownership ($INST$), the composition of the board of directors ($BINDEP$) and the proportion of financial experts on the audit committee ($AUDIT\_FE$). Additionally, we control for *disclosure characteristics*, by including controls for horizon ($GUIDE\_H$), specificity ($GUIDE\_S$), and supporting information ($SUPPORT$). Finally, following Ball et al. (2012), we also control for market value of equity (MVE), leverage (LEV), book-to-market (BTM), number of analyst following (AF), and stock return volatility (RET_VOL). Appendix B contains all variable definitions.

As noted above, we measure analysts' and market reactions to management forecasts using a number of measures. Next, we explain our proxies for each of these constructs in turn.

Analysts' reactions to management forecasts

Our first proxy for analysts' reaction to management forecasts is AF_CORR, which measures the change in analysts' forecasts five days after the issuance of a management forecast,[16] and is calculated as the change in the absolute difference (scaled by lagged quarter closing price) between EPS mean consensus estimate and management forecast before and after guidance, multiplied by minus one. A positive (negative) value indicates a correction of analysts' mean forecast towards (away from) the management forecast. Our second proxy is ΔAF_ERROR that indicates the change in analysts' forecast error five days after the issuance of management forecasts, where the forecast error is measured as the absolute value of the difference between mean estimate and the actual EPS for that quarter scaled by lagged quarter closing price. A negative (positive) value indicates a decrease (increase) in analysts' forecast error. Our third proxy is DIS_AFTER, which indicates analysts' estimates dispersion and is measured as the standard deviation of analysts' forecasts after a management forecast, a larger value implies greater disagreement among analysts.[17]

In model (6), we expect β_1 and β_3 to be positive (negative) when the dependent variable is AF_CORR (ΔAF_ERROR), suggesting greater reaction to forecasts made by more conditionally conservative firms and also, a greater reduction in analysts' forecast error. Finally, if management forecasts are informative, β_2 will be positive (negative) when the dependent variable is AF_CORR (ΔAF_ERROR), and we should observe a larger coefficient for bad news forecasts in accordance with the idea that bad news are inherently more credible (Mercer, 2004; Hutton et al., 2003). When the

[16] Consistent with Cotter et al. (2006), in our sample around 45% of analysts revise their forecasts within five days of earnings guidance. Longer windows have also been used in prior work (see e.g. Pae et al. (2016)). Our results are robust to using ten, fifteen and twenty days within earnings guidance as alternatives.

[17] Results are consistent if we use the median consensus estimate to calculate AF_CORR and ΔAF_ERROR.

dependent variable is DIS_AFTER, we expect β_1 and β_3 to be negative, indicating more agreement among analysts after forecasts made by more conditionally conservative firms and β_2 to be positive as analysts might react differently to the same forecast.

A natural question that arises at this point is whether analysts incorporate conditional conservatism into their earnings forecasts, and how this might affect their reaction to management forecasts. If analysts fail to incorporate conditional conservatism into their earnings forecasts either due to lack of motivation or lack of ability, we risk finding a mechanical relation between analysts' reaction to management forecasts and conditional conservatism, because analysts' forecast errors would be systematically biased for more conservative firms. Prior research tackles this question, helping to dispel this concern, as it suggests that analysts are sophisticated users of accounting information that do understand the effects of conditional conservatism on reported earnings. A number of prior studies show that, although a certain heterogeneity exists in terms of the degree to which analysts understand complex accounting transactions, on aggregate, analysts' forecasts incorporate the effects of conservatism (Heflin et al., 2015; Jung et al., 2017), and for example, that late-in-the period forecasts are not different for more conservative firms. Helbok and Walker (2004) argue that when reported earnings are conservative analysts face a dilemma, whether to forecast reported or 'sustainable' earnings. They claim that analysts solve this dilemma by focusing on 'sustainable' earnings early in the year and then revising the forecast to incorporate any information that reflect the impact of any transitory items. More recent research by Louis et al. (2014) is in line with Helbok and Walker (2004), while Sohn (2012) results suggest that end of period analyst forecast errors for more conservative firms are not different from those of less conservative firms.

Despite the reassurance provided by this literature, to ensure that we control for this possibility, we follow this prior work and when estimating analysts' reaction to management forecasts, we include two additional controls in model (6). First, we control for the level of forecast error before a management forecast (FE_BEFORE) to account for systematic analysts' forecast biases associated with conditional conservatism (Helbok and Walker, 2004; Louis et al., 2014). Second, we control for abnormal accruals (AB_ACC) because Abarbanell and Lehavy (2003) argue that firm reporting choices affect analysts' forecast errors. In particular, they show that the recognition of unexpected accruals is associated with asymmetries in forecasts errors distributions.[18]

[18] A greater number and magnitude of extreme optimistic analyst forecasts relative to pessimistic forecasts, and higher incidence of small pessimistic relative to small optimistic analyst forecasts.

Market reaction to management forecasts

Following previous research (Mercer, 2004; Hutton et al., 2003; Ng et al., 2013), we measure market reaction to management forecasts by studying cumulative abnormal returns (CAR) over the 3-day window surrounding the forecast date. CAR is estimated using the market model.[19]

To the extent that conditional conservatism increases forecast credibility we expect β_1 in model (6) to be positive (negative) and significant for good (bad) news forecasts, when the dependent variable is CAR. If management forecasts are informative we expect β_2 to be positive (negative) for good (bad) news forecasts. We also expect β_2 to be larger for bad news relative to good news forecasts, indicating the former are more credible (Mercer, 2004; Hutton et al., 2003). Finally, we expect a positive (negative) and significant β_3 for good (bad) news forecasts, capturing the market reaction beyond that generated by the magnitude of the forecast (i.e. increased credibility that can be attributed to conditional conservatism).

2.4 Sample and Results

We collect management forecast data from I/B/E/S Guidance, financial data from Compustat, securities data from CRSP, analyst coverage data from I/B/E/S and institutional ownership information from Thomson Reuters 13F.[20] After imposing all data requirements for the estimation of model (5), our final sample consists of 3,056 US publicly-listed firms over the period 1997-2014, and 94,134 firm-quarter observations. We winsorize continuous variables at the 1% and 99% of their distributions to mitigate concerns regarding outliers.

Table 1 presents descriptive statistics of our sample firms. Panel A shows that firm-quarter observations are evenly distributed across years and conservatism ranks. Panel B reports the distribution of firms and quarterly EPS management forecasts by year. Around 80% of our sample firms issue at least one forecast during the period, of which 30.39% are good news and 68.96% are bad news. The number of forecasts increases significantly during the first years of our sample period and specially after the passage of Reg. FD in August 2000. We introduce year fixed-effects in our models to account for these time trends. Throughout the period, the proportion of bad news forecasts doubles that of good news forecasts. This is consistent with managerial use of forecasts to issue early warnings to avoid litigation risk and reputation costs (Skinner, 1994) and also, to lower analysts' expectations to facilitate

[19] We obtain qualitatively similar results when CAR is calculated from a four factor model and/or using a 5-day window around the forecast date.

[20] Because I/B/E/S provides analyst and management forecasts based in their own version of earnings (i.e. street earnings) we also use I/B/E/S actual earnings rather than Compustat actual earnings to avoid introducing measurement error in our dependent variables.

beating analysts' forecasts subsequently (i.e., earnings guidance) (Matsumoto, 2002). This evidence is also consistent with limited disclosure of good news, potentially, because of lack of credibility or to avoid loss of competitive advantage. The patterns observed are also consistent with evidence in Chuk et al. (2013) suggesting Thomson First Call's Company Issued Guidance (CIG)[21] database coverage is incomplete and biased towards bad news management forecasts.[22] Panel C shows the number of unique firms by the number of forecast issued in our entire sample period. There are 1,489 (779) firms that do not issue good news (bad news) guidance and 633 firms that do not issue guidance. Panel C also shows that around 51% (75%) of sample firms issue a good news (bad news) management forecast in at least one quarter. Most sample firms issue guidance with high frequency. In fact, 9% (21%) of them issue good news (bad news) management forecasts in ten or more quarters. Panel D confirms that firms issue more bad news forecasts on average. The average firm issues bad news forecasts in nine quarters, and good news forecasts in four quarters.

Table 1 Panel E reports quarterly EPS management forecasts by conservatism rank. The univariate relation between management forecast frequency and conservatism appears to be negative. However, this evidence does not control for other determinants of management forecast frequency. We explore those in Panel G. This also may explain the positive (negative) univariate association between conditional conservatism and bad news (good news) voluntary disclosure. Panel F show that our final sample is composed mostly of large and profitable firms, and that the distribution of our conservatism measure is similar to the distribution of the entire estimation sample.[23]

Table 1 Panel G shows mean values of selected variables by conservatism rank. First, we consider the distribution of *situational incentives* variables. On average firms in the top deciles of conditional conservative are slightly more financially distressed, have less litigation concerns, and have more insider stock and options acquisitions relative to firms in the bottom decile. There is no significant difference regarding market concentration. More financially distressed firms have greater incentives to issue misleading management forecasts because the benefits (costs) associated with inaccurate forecasts are higher (lower) (Mercer, 2004; Koch, 2002). Second, we examine *management credibility.* Accuracy is fairly constant across groups, although firms in the top deciles of conditional conservatism score slightly lower in managerial credibility. Third, *internal and external assurance* variables indicate that on average more conditionally conservative firms have lower institutional ownership. There is no significant difference in board independence. Importantly, *guidance characteristic* variables indicate

[21] I/B/E/S Guidance was merged with First Call CIG, after the acquisition of First Call by Thomson.

[22] Our main results are robust to limiting the early years in our sample (i.e. excluding observations prior to 1999) and to limiting our sample only to firms covered by I/B/E/S.

[23] See Appendix A, Table A2.

that more conditionally conservative firms issue guidance slightly later in the period, and issue more guidance on additional measures (e.g. revenue forecasts) relative to less conservative firms. This is consistent with conditionally conservative firms issuing differential guidance, and with these firms disclosing more information (providing guidance on additional measures, such as revenue), consistent with the complementary hypothesis.

Regarding the distribution of other variables over conservatism rank, we find that firm size, return on assets, analyst following and abnormal accruals are monotonically decreasing on conservatism rank, while book-to-market is monotonically increasing in conservatism rank. Leverage is higher for firms in the top decile relative to firms in the bottom decile. These associations are consistent with prior theoretical and empirical predictions (Watts, 2003; LaFond and Watts, 2008; Khan and Watts, 2009), further validating CO_RANK as a good measure of conservatism in our sample. Finally, we observe that analysts forecast error before guidance is increasing in conservatism rank. These results are consistent with Abarbanell and Lehavy (2003) concern that analysts' forecast biases may be associated with firm reporting choices and confirms the importance of include FE_BEFORE as a control variable in our multivariate analysis of analysts and market reactions to management forecasts.

Overall, the evidence in Table 1 serves to validate our conditional conservatism proxy and suggests that it is unlikely that it spuriously captures other determinants of management forecasts' credibility. It also ratifies the need to control for the determinants of credibility in our analyses and offers some preliminary evidence that conditional conservatism and managerial voluntary disclosure through management forecasts act as complements.

2.4.1 Conditional Conservatism and Management Forecasts Frequency

Table 2 reports the results for the estimation of model (5).[24] The coefficient on CO_RANK for good news forecasts (columns 1 and 3) is significantly positive, while for bad news forecasts (columns 2 and 4) is significantly negative. Consistent with H1, this result suggests a positive (negative) association between conditional conservatism and good news (bad news) voluntary disclosure.

In terms of economic magnitude, other things equal, moving from the bottom to the top decile of conditional conservatism implies an increase in the probability of issuing good news forecasts of 2.42% (column 1). The probability of issuing a good news earnings forecasts in a given quarter for our sample equals 8.6%, which means that firms in the top decile of conditional conservatism are 28.13% (2.42%/8.6%) more likely to issue good news than firms in the bottom decile. For bad news earnings

[24]In Table 2 the dependent variables were multiplied by 100, so the coefficients on CO_RANK is interpreted as percentages.

forecasts (column 2) moving from the bottom to the top decile of conservatism implies a decrease in the probability of issuing bad news of 6.02%. This can be interpreted as firms in the top decile of conditional conservatism being 31.03% (6.02%/19.4%) less likely to issue bad news. Regarding forecast regularity (columns 3 and 4), moving from the bottom to the top decile entails a 29.49% (24.32%) increase (decrease) in good (bad) news regularity.[25] This suggests the effect of conservatism is economically large.

As expected, the coefficient on $SIZE$ is positive, indicating that larger firms issue more earnings guidance. The coefficient on BTM is positive for good news and negative for bad news, indicating that growth opportunities are negatively (positively) associated with good (bad) news disclosure. Firms with higher ROA are less (more) likely to issue good (bad) news forecasts. The coefficient on AF is positive and significant consistent with an increased demand for forward-looking disclosure in firms with more analyst following. The coefficient on $INST$ is positive as expected, and significant for both good and bad news forecasts. Consistent with S_EARN, DIS and RET_VOL being surrogates for the difficulty of predicting earnings we observe negative coefficients as predicted by prior literature. The coefficient on BID_ASK is positive, consistent with firms issuing more earnings guidance when information asymmetries are higher. Finally, firms with higher AB_ACC are less (more) likely to issue good (bad) news forecasts.

To further tease out if the reason why more conditionally conservative firms issue more good news earnings forecasts is to disclose good news (particularly, difficult-to-verify expected future profits), we look at the association between conditional conservatism and good news voluntary disclosure when future good news is anticipated (i.e. positive RET_{t+1}).[26]

Table 3 presents evidence on the moderating effect of future stock market returns over the association between conditional conservatism and voluntary disclosure of good news. The results indicate that the association between conservatism and good news forecasts (column 1) is stronger in anticipation of one-quarter ahead stock returns, whereas no such association is found for bad news management forecasts (column 2). In terms of economic significance, other things being equal, one standard deviation increase in future stock returns means an additional 0.58% increase in the likelihood of issuing a good news forecast for a firm moving from the bottom to the top decile of our measure of conservatism. Overall, this test provides evidence consistent with conditional conservatism enabling truthful good news disclosure.

[25] Results in columns 3 and 4 are robust to estimating model (5) using a orderer probit panel data approach.

[26] Results are robust to alternatively using expected returns from the market model or the four-factors model.

2.4.2 Conditional Conservatism and Management Forecasts Credibility

Thus far, our results indicate that conditional conservatism influences the frequency of good and bad news management forecasts, and that good news forecasting in conditionally conservative firms is associated with future positive returns. Next, we focus on the credibility of these forecasts.

First, we look at analysts' reaction to management forecasts. Figure 1 plots the univariate relation between analysts' reactions and management forecasts. Figure 1.1 shows that analysts' corrections after management forecasts monotonically increase in conditional conservatism whereas Figure 1.2 shows that analysts' forecasts errors after guidance monotonically decrease in conditional conservatism. This evidence suggests that management forecasts made by more conditionally conservative firms trigger a stronger reaction (in the expected direction). This is consistent with prior literature indicating that analysts are concerned about the accuracy of their earnings forecasts and seek to minimize forecast errors (Stickel, 1992; Mikhail et al., 1999; Hong and Kubik, 2003).

To provide further evidence on whether conditional conservatism increases the credibility of management forecasts, we also analyze market reactions to such forecasts. Figure 2 plots mean cumulative abnormal returns around the day of the management forecast for firms in the top and bottom decile of our conservatism measure.[27] Figures 2.1 and 2.2 plot mean market reactions to good and bad news management forecasts, respectively. Both figures reveal a stronger market reaction to forecasts made by more conservative firms. The effect is around 2 basis points larger for forecasts made by firms in the top rank of conservatism relative to firms in the bottom rank.

Table 4 presents the results from a formal test on the links between conditional conservatism and the credibility of management forecasts (model (6)).[28] Table 4 Panel A shows the results for good news management forecasts. When the dependent variable is AF_CORR (columns 1 and 2), we find a positive and significant coefficient of 0.327 (column 2) on the interaction term ($N\_SIZE{*}CO\_RANK$), indicating that analysts' revisions in reaction to forecast news increase with conditional conservatism, consistent with H2. In terms of economic magnitude, a one standard deviation change in N_SIZE implies a 29.72% incremental analyst revision for good news forecasts issued by firms in the top decile of CO_RANK relative to firms in the bottom decile. We also find a negative and significant coefficient for $N\_SIZE{*}CO\_RANK$ when the dependent variable is ΔAF_ERROR (columns 3 and 4), indicating that the reduction in analyst forecast errors after good news management forecasts is larger for more conditional conservative firms. The coefficient of -0.234 on $N\_SIZE * CO\_RANK$ (column 4) implies

[27] In Figure 2 CAR is calculated using the market model but we get similar patterns when using the four-factor model.

[28] Untabulated univariate results indicate, for both types of news, that conditional conservatism is positively (negatively) associated with AF_CORR (ΔAF_ERROR) consistent with the patterns described in Figure 1.

that the reduction in analyst forecast error, for one standard deviation change in N_SIZE, is 21.27% larger for good news forecasts issued by firms in the top decile of CO_RANK relative to firms in the bottom decile. Finally, Panel A, columns (5) and (6) presents the results on the association between analysts' estimates dispersion after management forecast (DIS_AFTER) and conditional conservatism. The coefficient on N_SIZE is positive, while the coefficient on $N\_SIZE * CO\_RANK$ is negative (both significant). These results are consistent with analysts having different abilities to incorporate new information into their forecasts, and conditional conservatism helping to reduce disagreement among them.

After controlling for the effects of situational incentives, management credibility, internal and external assurance, disclosure characteristics (Mercer, 2004), the magnitude of the forecast news (Jennings, 1987; Ng et al., 2013) and the plausible *ex-ante* bias in analysts' forecasts due to conditional conservatism (Abarbanell and Lehavy, 2003), we find that the reaction of analysts to management forecasts increases considerably for more conditionally conservative firms. This is consistent with conditional conservatism increasing the credibility of management forecasts and the complementary prediction: i.e., conditional conservatism allows other sources of information to 'flourish' (LaFond and Watts, 2008).

Panel A columns (7) and (8) presents evidence on the association between conditional conservatism and cumulative abnormal returns. The coefficient on N_SIZE is positive and slightly statistically significant. However the coefficient on $N\_SIZE * CO\_RANK$ is positive and significant, indicating that the market reacts beyond the magnitude of forecasts news due to the increase in forecast credibility associated with conditional conservatism. In terms of economic magnitude, the coefficient of 3.519 (column 8) indicates that the market reaction to the magnitude of the forecast increases by approximately 3.19 basis points between the top and bottom deciles of conservatism for good news forecasts. These findings indicate a strong market reaction to good news management forecast issued by more conservative firms, in terms of cumulative abnormal returns.[29]

We obtain similar results for the bad news sample (Panel B), indicating that conditional conservatism adds credibility to both good and bad news management forecasts, consistent with H2. However, the coefficient on $N\_SIZE * CO\_RANK$ is larger in magnitude for good news relative to bad news management forecasts suggesting that the effect of conditional conservatism on credibility is greater for good news disclosure.

Regarding the control variables, N_SIZE is greater in magnitude and significance for bad news

[29]CAR in Table 4 is calculated using the market model but we obtain similar results if CAR is calculated using the four-factor model.

(Panel B) relative to good news (Panel A) in all specifications except when the dependent variable is DIS_AFTER. Indicating that bad news forecasts are *ex-ante* regarded as more credible (Skinner, 1994; Soffer et al., 2000). Regarding the *situational incentives* proxies, in most of the specifications the coefficients are not statistically significant, except for financial distress (FD) that appears to increase analyst dispersion, and inside trading ($INSIDE$) and market concentration (HHI) that are associated with weaker market reactions to management forecasts, both for good and bad news management forecasts. Consistent with *management credibility* effects on disclosure credibility, we find a positive (negative) association between $ACCURACY$ and AF_CORR (ΔAF_ERROR) for both good and bad news forecasts. For the CAR specifications, we find that $ACCURACY$ is associated with stronger (weaker) reactions for good (bad) news forecasts. These results are consistent with prior accuracy increasing disclosure credibility for good news forecasts but not for bad news forecasts.[30] Coefficients for *internal and external assurance* control variables are mostly not statistically significant except for $INST$ and $AUDIT\_FE$ when the dependent variable is AF_CORR (or ΔAF_ERROR), in both cases the sign of the coefficient is contrary to what was expected. Finally, for *guidance characteristics* control variables more precise forecasts are associated with larger analyst revisions (AF_CORR), but also with increased forecast errors (ΔAF_ERROR). In addition, guidance made early in the period are associated with lower analyst estimate dispersion after the forecast (DIS_AFTER), but also with increased forecast errors (ΔAF_ERROR).

Taken together, these results suggest that conditional conservatism is associated with higher voluntary disclosure of good news, and enhanced credibility of management forecast. Further, more conditional conservative firms are able to elicit a stronger analyst/market reaction. Overall, this evidence is consistent with both H1 and H2, and suggests that conditional conservatism complements voluntary disclosure of managerial private information through management forecasts, particularly, good news disclosure.

2.5 Endogeneity Concerns

A potential concern with our empirical design is endogeneity arising from potential correlated omitted variables. We take several steps to address this concern. First, we take the three- and five-year average of Khan and Watts (2009) measure of incremental timeliness to bad news (C_SCORE) as our proxy for conservative accounting. This measure is likely to be predetermined for current managers (García Lara

[30] A potential explanation may be that managers guide analysts' forecasts downwards and manipulate earnings upwards to avoid negative earnings surprises (Matsumoto, 2002), this actions taken by manager will result in more accurate bad news forecasts and less market reactions to bad news forecasts if investors anticipate this behavior.

et al., 2016a). Consistent with this idea, prior research shows that conservative accounting is stable over time (Khan and Watts, 2009; Callen et al., 2010). Moreover, by construction C_SCORE varies with the determinants of conservatism (i.e. firm size, leverage and book-to-market) further mitigating endogeneity concerns. Second, we include in our models time- and industry-fixed effects to account for economic trends and unobservable time invariant industry-specific factors that might be confounding variables in explaining management earnings forecasts frequency and credibility. Third, we control for known determinants of management forecasts (Hirst et al., 2008) and their credibility (Mercer, 2004). We also control for corporate governance quality, because prior research suggests that it influences both conditional conservatism and voluntary disclosure (Eng and Mak, 2003; Ahmed and Duellman, 2007).

However, we cannot entirely rule out endogeneity. Ideally, to establish causality, we would require an exogenous and significant overhaul to existing conservatism in accounting regulation that was randomly assigned to firms. In the absence of such a shock, we conduct two additional analyses to attempt to better identify the causal flow. We discuss them in turn.

2.5.1 Conditional Conservatism and Management Forecasts around SFAS 142

We follow prior work and analyze a change in financial accounting standards as a plausible exogenous shock to conditional conservatism. In particular, we look at the adoption of SFAS 142. SFAS 142 replaces amortization of goodwill with an annual impairment test based on fair value with write-offs if the carrying amount of goodwill exceeds its implied fair value.[31] Roychowdhury and Watts (2007) argue that "to the extent that FAS 142 generates more impairment of goodwill, the consequence would be an increase in earnings timeliness with respect to negative returns" (p. 30). Cedergren et al. (2015) shows that SFAS 142 forces a greater degree of conditional conservatism into the reporting system relative to the previous regime (SFAS 121). The frequency of goodwill impairment increases after SFAS 142 (Li et al., 2011b), and measures of acquisition overpayment become better predictors of subsequent write-offs consistent with SFAS 142 increasing conditional conservatism (Cedergren et al., 2015).

To test this effect, we run the following model:

$$\begin{aligned} Y_t = &\beta_0 + \beta_1 * TREATED + \beta_2 * SFAS142 + \beta_3 * TREATED * SFAS142 \\ &+ \gamma * Controls_{t-4} + \epsilon_t \end{aligned} \tag{2.7}$$

[31] Goodwill and intangible assets acquired after June 30, 2001, will be subject immediately to the non-amortization and amortization provisions of this Statement.

where $TREATED$ is a dummy variable equal to one if the firm was involved in at least one M&A deal (as acquiror) before SFAS 142.[32] We define it in more detail below. SFAS 142 is a dummy variable equal to one for all observations after 2001-Q2, when SFAS 142 became effective, and zero otherwise. The coefficient of interest is the interaction term $TREATED * SFAS142$ that captures the effect on the treated of an exogenous increase in conditional conservatism. If conditional conservatism induces the expected associations, β_3 will be significant. Model (7) incorporates industry and year fixed effects, and standard errors are clustered at the firm level.

Given that goodwill is an intangible asset that arises when a firm acquires an existing business, firms that were never the acquiror part in an M&A deal will not have any goodwill to impair and will be less likely to be affected by SFAS 142. The firms likely affected are those involved in M&A deals pre-SFAS 142. We use the SDC Platinum database to collect data on M&A deals (i.e., the acquiring firm). Our sample includes all completed deals from January 1, 1995 through December 31, 2014 in which the acquiror is a U.S. publicly listed firms, and the percentage of target's outstanding shares acquired is at least 90%. After imposing data requirements to construct all variables, we identify 1,743 firms involved in at least one deal before SFAS 142. These 1,743 unique firms constitute our sample of firms that are most likely to be affected by SFAS 142.

Figure 3 plots the mean value of our conditional conservatism measure for treated and non-treated firms before and after SFAS 142.[33] As expected, there is a greater increase in conditional conservatism after SFAS 142 for treated firms. The change in the mean value is 0.026 (0.011) or a 28% (9.4%) increase for treated (non-treated firms). A t-test confirms that the mean difference in the change of conditional conservatism is statistically significant. For treated firms the increase in conditional conservatism is 0.0155 larger (t-value of 5.62) than in non-treated firms.

Table 5 Panel A presents the results of estimating model (7). Given potential systematic differences between treated and non-treated firms that might affect our dependent variable, we estimate model (7) using a control sample matched in $SIZE$, LEV, BTM, ROA and AF before SFAS 142. We use a standard propensity score matching approach.[34] We also require control and treated firms

[32] Two potential concerns with this analysis are the next. First, impairment of goodwill was required before SFAS 142; however, this was not a common practice with most firms amortizing goodwill over 20-40 years and not many firms recording impairments (Roychowdhury and Watts, 2007). Second, conditional conservatism may be systematically associated with M&A. Francis and Martin (2010) show that conditionally conservative firms make more profitable acquisitions, and less post-acquisition divestitures. This implies that conditionally conservative firms are less likely to impair goodwill, because they take better investment decisions ex-ante. To the extent that $TREATED$ may capture M&A deals made by acquirors that were already conservative, it will make finding an effect harder.

[33] We show the mean value of C_SCORE_3y instead of CO_RANK for illustration purposes only, as is clear to see the change in the three-year average relative to the rank.

[34] We implement a nearest-neighbor matching using a logit regression without replacement, and with a 0.001 caliper tolerance.

to belong to the same industry. As expected, we obtain a positive and significant coefficient on TREATED*SFAS 142 when our dependent variable is $GUIDE\_GN$ but not for $GUIDE\_BN$.[35] In terms of economic significance, conditional conservatism increases the probability of issuing good news forecasts by 2.269% (column 1). These results support our prediction that conditional conservatism is positively associated with good news earnings forecasts.

Panel A columns (3) to (10) shows the effect on good news forecasts credibility. We find an increased analyst response beyond forecast news due to the increase in conditional conservatism, except for DIS_AFTER, and we also find a marginally significant increased market response for good news forecasts. A potential explanation for not finding stronger results supporting H2 is that the group of treated firms were less conservative before SFAS 142, and after treatment they become more conservative getting closer to the level of conservatism of non-treated firms (see Figure 3.1). Table 5 Panel B shows the balanced properties of the matching procedure.

Finally, we present evidence consistent with the parallel trends assumption. Figure 3.2 shows that before treatment both treated and control firms follow a similar path with respect to $GUIDE\_GN$. We observe in the graph that for the year following the treatment $GUIDE\_GN$ increase slightly more for treated firms. Figure 3.2 also suggests for the remaining years in our sample $GUIDE\_GN$ follows a similar trend for both treated and non-treated firms, with $GUIDE\_GN$ being on average greater for treated firms. Another way to verify that the pre-treatment parallel trends assumption is not violated is to introduce leads and lags for the implementation of treatment in model (7). Finding positive and significant lead coefficients would be evidence against the pre-treatment parallel trends assumption. We re-estimate model (7) introducing lead/lags for the implementation of SFAS 142. Figure 3.3. shows that the estimated coefficients on TREATED*YEAR are not statistically significant different from zero for years prior to SFAS 142, indicating that the difference in the frequency of good news voluntary disclosure between the treatment and control groups did not exist before the implementation of SFAS 142, in other words, it is reasonable to accept the pre-treatment parallel trends assumption.

Overall, given the restrictions imposed on our sample by this test, we do not consider it our main analysis, but it provides confirmatory evidence in support for our main analyses. Taken together, the results in Table 5 provide some assurance that conditional conservatism increases the issuance of good news management earnings forecasts and their credibility.

[35]Untabulated results indicate qualitative similar results for MF_REG_GN and MF_REG_BN

2.5.2 Shock to Overall Credibility

To provide further assurance on our credibility tests, following Lins et al. (2017) we exploit the Enron/Worldcom scandal and the 2008-2009 financial crisis as periods during which the overall level of credibility in firms and capital markets plummet unexpectedly (i.e. shocks to credibility). During low-trust periods investors and shareholders are likely to be more concerned with the credibility of the information they relied on to make investment decisions in the past, and will look for signals indicative of firms trustworthiness (Guiso et al., 2008; Lins et al., 2017). Accordingly, we expect management earnings forecasts issued by more conservative firms to elicit a stronger market reaction during "unexpectedly low-trust" periods, when credibility is more valuable, consistent with H2.

To test this prediction, and given that prior literature does not explore the effects over analysts of such crises, we follow the method in Lins et al. (2017) as precisely as possible in both the definition of crisis of trust periods and the choice of dependent variable. In particular, we focus exclusively on market reactions, following their approach. Lins et al. (2017) define two periods of low-trust: (1) the accounting frauds and bankruptcy of Enron and Worldcom, which begins in October 2001 (when Enron first admitted accounting violations) and ends in March 2003 (the month before the U.S. stock market recovery); and (2) the 2008-2009 financial crisis. The "Financial Crisis" begins August 2008 (the month before Lehman Brothers bankruptcy) and ends March 2009 (when the S&P 500 reach the lowest point during the crisis). Using these shocks, we estimate model (6) for crisis and non-crisis of trust periods. Our dependent variable is the CAR over a 3-day window around good news management forecast date. Consistent with H2 we expect β_3 to be positive and statistically significant, and larger for crisis of trust periods relative to non-crisis periods.

Table 6 presents the results. N_SIZE is positive and significant in column (1), indicating that during non-crisis periods good news forecasts are regarded as informative, $N\_SIZE * CO\_RANK$ is also positive and significant as in our previous tests. During crisis of trust periods, in columns (2) to (4) we find a negative and significant coefficient on N_SIZE, for two out of our three regressions. This suggests markets apply a discount to management forecast news when there is a shock to the overall level of credibility. Importantly, we find a positive and significant coefficient on $N\_SIZE{*}CO\_RANK$, indicating that even during crisis of trust periods management forecasts issued by more conditional conservative firms remain credible. The effect is stronger for the financial crisis period relative to the Enron/Worldcom period. In terms of economic significance, if we consider the financial crisis period (column 3), one standard deviation in N_SIZE is associated with a market reaction of -2.41 basis points for firms in the bottom decile of conditional conservatism against a 8.92 basis points market reaction for firms in the top decile of conditional conservatism. Also we find that the coefficient on $N\_SIZE * CO\_RANK$ is significantly larger for crisis of trust periods relative to the non-crisis period, as expected.

Taken together, the results in Table 6 indicate that conditional conservative firms are more resilient to credibility shocks, and that the benefits of conditional conservatism are not limited only to crisis of trust periods. The findings are consistent with the idea that conditional conservatism is more valuable when overall credibility decreases unexpectedly, as trustworthiness is highly valued by the market in these periods.

2.6 Additional Analysis

In this section, we provide additional evidence supporting our main results by examining specific settings where we expect the effects of conditional conservatism to be greater. We further report on some final robustness checks (most of them have been discussed as we explained our main results).

2.6.1 Management forecasts and the firm information environment

Prior literature suggests a more important role for conservatism when the information environment of the firm is weaker (LaFond and Watts, 2008; García Lara et al., 2016b). Following Duchin et al. (2010), we build a composite index of information asymmetry (IA) as the mean of the standardized values of seven variables related with firms' information environment: (1) minus one times the number of analyst covering the firm each quarter; (2) analyst forecast dispersion; (3) analyst forecast error; (4) number of firms' segments; (5) percentage of intangible assets; (6) the average of daily Bid-Ask spread over the last four quarters; and (7) stock return volatility.

We partition our sample using IA. Firms in the bottom (top) tercile of IA are classified as firms with low (high) information asymmetries. If the benefits of conservatism are higher in settings where information asymmetry is more severe, we expect the coefficient on CO_RANK to increase in the terciles of IA for good news management forecasts.

Table 7 presents the results. Consistent with IA capturing different aspects of the firm information environment (e.g., operating complexity/fundamental uncertainty/cost of acquiring information for outsiders) and with prior research, we find that the coefficient on CO_RANK increases in IA, both in magnitude and significance, for $GUIDE\_GN$ (columns 1 to 3).[36] We find equivalent results when

[36]Untabulated results shows that more conditional conservative firms issue less bad news management forecasts except when firms face high information asymmetries.

consider analyst/market reactions (columns 4 to 15), with the exception of DIS_AFTER, $N\_SIZE * CO\_RANK$ increases in magnitude and significance with IA terciles.

2.6.2 Bundled Forecasts

Anilowski et al. (2007) document a steady increase in the use of bundled forecasts (i.e. forecasts issued together with earnings announcements) over the period 1994-2004. In line with this prior research, bundled forecasts are predominant in our sample (approx. 67%). Rogers and Van Buskirk (2013) argue that the traditional approach to measure forecast news (i.e. forecast value minus analysts' expectations) is inadequate to measure news for bundled forecasts, given that analysts are likely to revise their expectations about future earnings after current earnings announcement. Failing to account for such changes in expectations might bias the measure of forecast news and lead to misclassification of forecasts. Additionally, when the management forecast is issued contemporaneously with earnings announcements it is harder to disentangle the effect of the forecast from that of the earnings news.

According to Rogers and Van Buskirk (2013), the correct way to measure forecast news for bundled forecasts is to estimate analysts expectations conditional on the information conveyed by current earnings announcements, calculated as follows:

$Conditional \quad Expectations(E[X_{t+1}|X_t]) = E[X_{t+1}] + AnalystRevision$

$Forecast \quad News = f[X_{t+1}] - E[X_{t+1}|X_t]$

Rogers and Van Buskirk (2013) propose and validate this method for estimating analyst conditional expectations. They generate predicted analysts' revisions by estimating a model of observed analysts' revisions for firms not issuing management forecasts: for this group the revision can be attributed to current earnings announcements. Then, the estimated coefficients are applied to the group of forecasting firms, to obtain a prediction on how analyst would have revised their earnings estimates absent management forecast.

We follow two approaches to account for the potential effect of bundled forecasts in our results. First, we follow Rogers and Van Buskirk (2013) procedure to calculate predicted analyst revisions, and bundled forecasts news, and re-estimate models (5) and (6), controlling for current earnings surprises ($SURPRISE$) for bundled forecasts. $SURPRISE$ is defined as the difference between actual EPS and the most recent analyst estimate. Second, we re-estimate models (5) and (6) considering only non-bundled forecasts. None of the two approaches is perfect, Rogers and Van Buskirk (2013) procedure may potentially introduce measurement error biasing the results, while excluding bundled forecast reduces the sample size likely reducing the power of our tests.

Table 8 replicates the analysis in Table 2 and Table 4 for good news forecasts. Columns (1) to (5) show the results for the Rogers and Van Buskirk (2013) approach. The coefficients on CO_RANK remains positive and significant when the dependent variable is $GUIDE\_GN$ (column 1). In addition, our results regarding forecasts credibility (columns 2 to 5) are robust to applying Rogers and Van Buskirk (2013) procedure, except for DIS_AFTER. As expected, $SURPRISE$ is significant in most of the cases. Our results remain robust if we consider only non-bundled forecasts (columns 6 to 10), except for ΔAF_ERROR.

Taken together, these results suggest that our inferences are generally robust to accounting for the effects of bundled forecasts.

2.6.3 Market Reaction to Earnings Announcements

Bertomeu and Marinovic (2016) argue that when soft signals are perceived as 'fully credible' markets should not react to any hard report of the same information released *ex-post*, as any information contained in the verified signal should have been anticipated by the market. However, if the signal is not 'fully credible' the market will react, to a certain extent, to an *ex-post* verified signal (Crawford and Sobel, 1982).

If conditional conservatism increases management forecast (i.e., the soft signal) credibility, we expect that the market reaction to earnings announcements (i.e., the *ex-post* verified signal) to be lower for more conditional conservative firms. In other words, the market reaction to earnings announcements is expected to be weaker for more conditional conservative firms as this information is impounded into prices to a greater extent when management forecasts are issued.

To test this prediction we estimate the following model separately for good and bad news management forecasts:

$$EA\_CAR_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * SURPRISE_t + \gamma * Controls_{t-4} + \epsilon_t \tag{2.8}$$

where EA_CAR measures cumulative abnormal returns over a 3-day window around the earnings announcement date, and are estimated using the market model and alternatively the four-factor model. CO_RANK, $SURPRISE$ and $Controls$ are all as previously defined. If our prediction is correct we expect β_1 (β_2) to be negative (positive) and significant.[37]

Table 9 shows the results of estimating model (8). We find a negative and significant β_1 for good news forecasts, indicating that the market response to earnings announcements is weaker for more

[37]We do not include N_SIZE and $N\_SIZE * CO\_RANK$ in this specification because the effect of the news size and its credibility is embedded in $SURPRISE$. However, untabulated analysis indicate that including N_SIZE and $N\_SIZE * CO\_RANK$ do not change our results.

conditional conservative firms. For bad news forecasts β_1 is negative but not statistically significant. As expected the β_2 is positive and significant for both, good and bad news forecasts, indicating that the larger the earnings surprise the stronger the market reaction. These results are consistent with our prediction that conditional conservatism increases credibility of good news management forecasts.

2.6.4 Managerial Overconfidence

Managerial overconfidence (i.e., managerial tendency to overestimate future returns from firms' projects) is potentially a confounding variable in our analyses. Prior literature documents that overconfidence affects both conditional conservatism, and management forecasting. In particular, Ahmed and Duellman (2012) argue that the tendency to overestimate (underestimate) the likelihood and size of positive (negative) shocks to future cash flows will be reflected in accelerated (delayed) gain (loss) recognition. This implies that overconfident managers are less likely to engage in conditional conservative financial reporting. Regarding management forecasting, Hribar and Yang (2016) predict and find evidence that overconfident managers are more likely to issue and subsequently miss their own earnings forecast. This is mainly because overconfident managers are a) more optimistic about firm future performance, b) more confident in their ability to predict future firm performance, and c) underestimate the likelihood of uncertain outcomes.

Thus, prior research indicates that managerial overconfidence is associated with lower conditional conservatism and with higher frequency and lower credibility of management earnings forecasts. Thus, not controlling for managerial overconfidence could plausibly bias our results. [38]

We follow prior literature and use CEOs option-exercise behavior to proxy for managerial overconfidence (Malmendier and Tate, 2005; Campbell et al., 2011; Hribar and Yang, 2016). CEOs are exposed to their firm's idiosyncratic risk, and thus, exercising options early, after vesting, is a mechanism CEOs have to reduce the exposure to this kind of risk. However, overconfident CEOs are more likely to delay option exercise because they believe the stock price will continue to outperform the risk free rate (Malmendier and Tate, 2005).

Following Campbell et al. (2011) and Ahmed and Duellman (2012) we use ExecuComp data to calculate the average percent moneyness of exercisable options, and classify a CEOs as overconfident if they hold stock options that are more than 67% in the money at least twice during our sample

[38] Regarding our first hypothesis, the managerial overconfidence argument implies that less conditional conservative firms are more likely to issue good news management earnings forecasts, which goes against our prediction that conservatism is positively associated with voluntary disclosure of good news information. Therefore, is unlikely that our findings supporting H1 are driven by managerial overconfidence. For our second hypothesis, the overconfidence argument suggests that management forecast issued by less conservative firms are likely less credible, in line with our prediction that conservatism is positively associated with the credibility of voluntary disclosure. Consequently, our second set of findings supporting H2 may be potentially driven by overconfidence.

period.[39] Our proxy for managerial overconfidence ($OVER$) is a dummy variable that takes the value of one for overconfident CEOs, staring the first fiscal year CEOs exhibit overconfident behavior (i.e. hold stock options more than 67% in the money), and zero for the rest of the sample.

Table 10 results indicate that more conditional conservative firms issue more good news management earnings forecasts, and that this forecast are associated with greater analyst and market reactions even after controlling for managerial overconfidence. This evidence alleviates concerns that our results are driven by managerial overconfidence.

2.7 Summary and Conclusions

We study whether conditional conservatism allows 'soft' sources of information to flourish as argued in LaFond and Watts (2008). Conservatism may attain this benefit because (1) it acts as a governance mechanism that reduces managerial incentives and ability to manipulate accounting earnings, and (2) it provides a benchmark for current performance that enables other sources of information to produce credible information.

We show that more conditionally conservative firms issue more good news earnings forecasts, and that good news forecasts are associated with greater market reactions for conditionally conservative firms, signaling greater credibility of disclosure. This is consistent with conditional conservatism acting as a mechanism that lends credibility *ex-ante* to voluntary disclosure by providing a "hard" reporting benchmark that allows outsiders to better evaluate the truthfulness of management forecasts. The results are robust to considering an exogenous shock to conditional conservatism (i.e. implementation of SFAS 142), and to using Rogers and Van Buskirk (2013) approach to measure the effect of bundled forecasts. We also verify that the association between conditional conservatism and good news earnings forecasts is moderated as theory would predict. We find a stronger (weaker) association when the firms face high (low) information asymmetries (LaFond and Watts, 2008; García Lara et al., 2016b). Additionally, we show that the association of conditional conservatism and market reactions to good news earnings forecasts is stronger during "crisis of trust" periods, when signals of credibility are more valuable (Lins et al., 2017; Guiso et al., 2008). Moreover, we show that market reaction to earnings announcements (i.e., the *ex-post* verified signal) is lower for more conditionally conservative firms issuing management forecasts (i.e. soft signals perceived as more credible).

We contribute to the conservatism literature by presenting empirical evidence on the benefits of conditional conservatism for firms information environment. We show that conditional conservatism

[39]We take as given Malmendier and Tate (2005) 67% moneyness cutoff, it cames from the calibration of stock options valuation model for undiversified executives.

is a mechanism by which managers can commit to truthfully disclose earnings forecasts. Second, we contribute to the debate on whether financial reporting and voluntary disclosure are complements or substitutes, by showing that conditional conservatism acts as a complement for timely voluntary disclosure of good news. By providing a “hard” reporting benchmark, conditional conservatism enhances the information value of good news earnings forecasts. Finally, our paper contributes to the literature on the determinants and characteristics of management forecasts by documenting that conditional conservatism increases the frequency and credibility of good news earnings forecasts.

Our evidence should be, however, interpreted considering the following caveats. First, the implementation of SFAS 142 may not be fully exogenous in the sense that it may be correlated with other concurrent relevant changes in regulation (e.g. Reg FD or SarbanesOxley). Second, potential measurement errors in our measure of conditional conservatism and coverage bias associated with I/B/E/S guidance database may result in unreliable inferences. Finally, our results may not generalize beyond the specific choices of our study. In particular, as we focus on management earnings forecasts the results may not be generalizable to other sources of ‘soft’ information.

APPENDIX A- Conservatism Measure

We replicate Khan and Watts (2009) main results. This appendix provides details on the estimation of our proxy for conditional conservatism. We follow Khan and Watts (2009) estimation procedure and delete all firm-years with negative book value of equity or total assets, and all firm-years with price per share less than \$1. Then we trim size, earnings, returns, leverage, market to book and depreciation at the 1% level each year. Khan and Watts (2009) estimate C_SCORE and G_SCORE using a sample of 115,516 firm-years observations between 1963 and 2005. Our sample is composed of 129,858 firm-years observations between 1968 and 2014.

Table A1 shows descriptive statistics for the variables used in the estimation, comparable to those in Table 1 of Khan and Watts (2009) which despite differences in the estimation period are fairly similar. We also report descriptive statistics of C_SCORE and G_SCORE as in Table 4 of Khan and Watts (2009). Again our results are comparable to those in Khan and Watts (2009). C_SCORE (G_SCORE) has a mean of 0.1147 (0.0247) and median of 0.1088 (0.0295), the first quartile (Q1) for both measures is positive, and there is a negative and significant correlation between C_SCORE and G_SCORE of similar size.

In Table A2 we show Fama-MacBeth coefficients from the estimation of model (6). The magnitude, sign and statistical significance is similar to those presented in Table 3 of Khan and Watts (2009). The mean adjusted R-square is also similar, we obtain an average of the adjusted R-squares from the 46 annual regressions of 19% and in Khan and Watts (2009) is 24%.

In Table A3 we show how mean ROA (NOACC) is monotonically decreasing (increasing) in C_SCORE, and the mean of ROA is negative for the most conservative firms, consistent with Table 6 results in Khan and Watts (2009).

Finally, in Table A4 we replicate Table 7 in Khan and Watts (2009), and show how our estimation of C_SCORE and G_SCORE show the same patterns. First, we replicate their results of how sorting on C_SCORE induces a reverse sort on G_SCORE. Second, we also replicate their result that market-to-book and size are decreasing, while leverage is increasing, in C_SCORE. Third, we also replicate their result that the length in investment cycle is increasing in C_SCORE.

Table A1: Descriptive Statistics

VARIABLES	N	Mean	SD	Q1	Median	Q3
Earn	143,291	0.0433	0.134	0.0106	0.0579	0.103
Ret	147,919	0.117	0.490	-0.196	0.0455	0.327
SIZE	162,215	5.046	2.115	3.440	4.915	6.520
MTB	162,214	2.563	2.874	1.004	1.666	2.924
LEV	163,871	0.641	1.083	0.0335	0.242	0.742
NOACC	119,087	-0.0181	0.0558	-0.0300	-0.00872	0.00205
CFOA	130,387	0.0709	0.133	0.0208	0.0809	0.141
INV_CYCLE	139,246	0.0443	0.0303	0.0244	0.0392	0.0579

	Mean	SD	Q1	Median	Q3
C_SCORE	0.1147	0.1157	0.0452	0.1088	0.1726
G_SCORE	0.0247	0.0460	0.0074	0.0295	0.0463
Pearson Correlation			-0.346***		
Spearman Correlation			-0.244***		

Descriptive statistics for 129,858 firm-years between 1968 and 2014. The number of observations(N), mean, standard deviation (SD), median and first(Q1) and third (Q3) quartiles are reported. All variables are winsorized at the 1% and 99 % level.

Table A2: Fama-MacBeth Coefficients from Estimation Regressions

Independent Variable	Predicted Sign	Coefficient	T-Stat
Intercept		0.0534***	4.11
D		-0.0138***	-3.34
Ret	+	0.0257***	3.42
Ret x SIZE	+	0.00151	1.17
Ret x MTB	-	-0.00188***	-2.57
Ret x LEV	-	-0.00430	-0.86
D x Ret	+	0.237***	13.20
D x Ret x SIZE	-	-0.0305***	-10.89
D x Ret x MTB	+	-0.00290*	-1.30
D x Ret x LEV	+	0.0558***	6.47
SIZE		0.00656***	6.96
MTB		-0.0105***	-7.80
LEV		-0.00354**	-2.05
D x SIZE		0.00121*	1.59
D x MTB		0.00108	1.28
D x LEV		0.00115	0.57
Mean Adj. R2		0.190	
Mean #Obs		2,763	

Fama-MacBeth coefficients from annual cross-sectional regressions of model(6), on a sample of 129,858 firm-years from 1968 to 2014. The dependent variable, X_i, is earnings scaled by lagged price, R_i are annual stock returns, and D_i is a dummy variable equal to one if returns are negative and zero otherwise. MTB is the market-to-book ratio, LEV is leverage, and SIZE is the natural logarithm of market value of equity. Mean Adj. R2 is the average of the adjusted R-squares from the 46 annual regressions estimated ***, **, * indicate significance at the 1%, 5%, and 10% levels.

Table A3: Distributions of ROA and NOACC, by C_SCORE Decile

	ROA			NOACC		
Decile	Mean	SD	Skew	Mean	SD	Skew
1	0.0822	0.101	-1.927	-0.0167	0.0480	-1.583
2	0.0715	0.0957	-1.963	-0.0172	0.0471	-1.434
3	0.0628	0.0979	-2.005	-0.0178	0.0508	-1.578
4	0.0518	0.106	-2.173	-0.0185	0.0523	-1.629
5	0.0424	0.107	-2.042	-0.0171	0.0522	-1.533
6	0.0321	0.114	-1.992	-0.0179	0.0547	-1.536
7	0.0206	0.117	-2.024	-0.0180	0.0565	-1.631
8	0.0102	0.116	-1.991	-0.0178	0.0564	-1.666
9	-0.00218	0.117	-2.023	-0.0167	0.0585	-1.515
10	-0.0132	0.102	-2.080	-0.0139	0.0580	-1.452

Mean, standard deviation (SD) and skewness (Skew) of ROA and NOAcc, by C_SCORE decile. The sample consists of 129,858 firm-years between 1968 and 2014. Firms are sorted annually into deciles by C_SCORE. ROA is is earnings before extraordinary items, deflated by lagged assets and NOACC is non-operating accruals, deflated by lagged assets.

Table A4: Mean of Selected Characteristics of C_SCORE Decile

Decile	C_SCORE	G_SCORE	MTB	SIZE	LEV	INV_CYCLE
1	-0.0310	0.0340	4.3043	7.8920	0.2656	0.0487
2	0.02703	0.0320	3.0313	6.8328	0.3079	0.0464
3	0.0556	0.0307	2.6938	6.1981	0.3348	0.0460
4	0.0778	0.0293	2.4803	5.6871	0.3535	0.0458
5	0.0977	0.0280	2.2490	5.2541	0.3871	0.0448
6	0.1172	0.0264	2.1206	4.8568	0.4255	0.0443
7	0.1384	0.0248	1.9600	4.4339	0.4945	0.0435
8	0.1634	0.0223	1.8609	4.0440	0.6010	0.0424
9	0.1996	0.0180	1.7561	3.6102	0.8362	0.0418
10	0.3019	0.0010	1.6738	3.2240	1.9845	0.0404

Means of selected characteristics of C_SCORE deciles. The sample consists of 129,858 firm-years between 1968 and 2014. Firms are sorted annually into deciles by C_SCORE, and the mean of the reported firm characteristics is calculated by decile. MTB is the market-to-book ratio, SIZE is the natural logarithm of market value of equity, LEV is leverage and INV_CYCLE is firm investment cycle.

APPENDIX B - Variable Definitions

Construct	Proxy	Name
Conditional Conservatism	Annual decile of the three-year (five-year) average of Khan and Watts (2009) measure of incremental timeliness to bad news *C_SCORE* (See Appendix A for details).	*CO_RANK*
Voluntary Disclosure	Dummy variable equal to one if the firm issue EPS guidance in quarter t and zero otherwise. We consider initial forecasts of the next quarters earnings issued within a window of (-90, 45) days, where day 0 is the fiscal quarter-end date.	*GUIDE*
Good News Disclosure	Dummy variable equal to one if EPS management forecast for quarter t is greater than analyst consensus estimate and zero otherwise.	*GUIDE_GN*
Bad News Disclosure	Dummy variable equal to one if EPS management forecast for quarter t is lower than analyst consensus estimate and zero otherwise.	*GUIDE_BN*
Good News Regularity	Categorical variable ranging from 0 to 4 indicating the number of good news disclosures over the last four quarters.	*MF_REG_GN*
Bad News Regularity	Categorical variable ranging from 0 to 4 indicating the number of bad news disclosures over the last four quarters.	*MF_REG_BN*
News Magnitude	Absolute value of the difference between management earnings forecasts (midpoint for range forecasts) and the most recent mean consensus analyst forecast.	*N_SIZE*
Forecast Revision	Analyst forecast correction measured as the change in the absolute discrepancy between analysts and management forecast (scaled by market price close at the end of the previous quarter) before and after management forecast. We multiply the change in absolute discrepancy (after minus before) by minus 1 so it indicates correction of analyst forecast towards management forecast.	*AF_CORR*
Forecast Error	Change in analyst forecast error is measured the change in the absolute difference between analysts EPS mean estimate and actual EPS (scaled by market price close at the end of the previous quarter) before and after management forecast.	Δ*AF_ERROR*
Forecast Dispersion After	Standard deviation of analyst forecast estimates in the estimates consensus for quarter t five days after management forecast.	*DIS_AFTER*
Abnormal Returns	CAR is defined as the sum of the estimated residuals from the market model (four factor model) in the 3-day window surrounding the management forecast date. The estimation periods runs from day -100 to day -30, where 0 is the day of the management forecast.	*CAR*
Firm Size	Natural logarithm of sales in quarter t. (COMPUSTAT item saleq).	*SIZE*
Growth Prospect	Book to market ratio, book value of equity (COMPUSTAT item ceqq) divided by market value of equity (COMPUSTAT item prccq times COMPUSTAT item cshoq).	*BTM*
Leverage	Long-term debt (COMPUSTAT item dlttq) divided by total assets (COMPUSTAT item atq).	*LEV*
Return On Assets	income before extraordinary items (COMPUSTAT item ibq) divided by total assets (COMPUSTAT item atq).	*ROA*
Analyst Following	Is natural log of one plus the number of analyst (IBES Summary item numest) following the company in quarter t. For companies not covered by IBES AF is set equal to zero.	*AF*
Institutional Ownership	Shares held by institutional investors as a percentage of total outstanding shares (Thomson Reuters 13F item instown_perc) in quarter t.	*INST*
Forecast Dispersion	Standard deviation of analyst forecast estimates in the estimate consensus for quarter t.	*DIS*
Earnings Volatility	Standard deviations of income before extraordinary items (COMPUSTAT item ibq) over the prior 20 quarters divided by average total assets (COMPUSTAT item atq) over the same period.	*S_EARN*
Cash-Flow Volatility	Standard deviations of operating cash flows over the prior 20 quarters divided by average total assets (COMPUSTAT item atq) over the same period. Quarterly operating cash flows are calculated as the difference of annual net operating cash flows (COMPUSTAT item oancfy) in quarter t and t-1 divided total assets (COMPUSTAT item atq) in quarter t.	*S_CFO*

(continue on next page)

APPENDIX B (cont'd)

Construct	Proxy	Name
Return Volatility	Standard deviation of daily returns without dividends over the last 250 trading days.	*RET_VOL*
Bid Ask Spread	Average of daily bid-ask spread over the quarter. Daily bid-ask spread is calculated as: 100*(ask-bid)/[(ask+bid)/2].	*BID_ASK*
Forecast Error Before	Is the absolute value of the difference between analysts EPS mean estimate and actual EPS (scaled by market price close at the end of the previous quarter) before the date of the management forecast.	*FE_BEFORE*
Unexpected Accruals	Unexpected accruals for quarter t are defined as total accruals minus normal accruals derived from a modified Jones Model (Jones, 1991) following Dechow et al. (1995) and Collins et al. (2014).	*AB_ACC*
Quarterly Stock Returns	Calculated as market price close at the end of the quarter (COMPUSTAT item prccq) divided by market price close at the end of the previous quarter minus one.	*RET*
Financial Distress	We use Farre-Mensa and Ljungqvist (2016) probability of default measure.	*FD*
Litigation Risk	Dummy variable equal to one if the firm belongs to a high litigation industry (SIC codes: 2833-2836;3570-3577;3600-3674;5200-5961;7370-7374;8731-8734).	*LIT*
Inside Trading	Is measured as the value of net inside trading over the ten day trading window around the management forecast date. We define insiders as all officers and directors within the firm and consider all transactions in firm's shares or options. We obtain insiders data from Thomson Reuters.	*INSIDE*
Market Concentration	Is measured using the Herfindal-Hirschman Index, which is equal to the sum of the squares of the market shares of the firms within an industry. Industry is defined as the four-digit SIC code.	*HHI*
Management Reputation	We measure manager reputation as the recursive average of the accuracy of all previous earnings management forecasts. Where accuracy is defined as the absolute value of the difference between the first management EPS forecast and the actual value of EPS, scaled by by market price close at the end of the previous quarter. Higher values indicate lower accuracy.	*ACCURACY*
Board Independence	Is defined as the proportion of independent directors within the board. We get board of directors data from BoardEx.	*BINDEP*
Audit Committee	Is defined as the proportion of directors with financial expertise within the audit committee. We get audit committee data from BoardEx.	*AUDIT_FE*
Guidance Horizon	Categorical variable ranging from 0 to 3. Taking value 0 if the management forecast was made between earnings announcement and 45 days after earnings announcement, 1 if the management forecast was made between 29 days before earnings announcement and earnings announcement,2 if the management forecast was made between 30 days and 59 days before earnings announcement and 3 if the management forecast was made between 60 days and 90 days before earnings announcement.	*GUIDE_H*
Guidance Specificity	Categorical variable ranging from 1 to 3. Taking value 1 if the management forecast is open-ended, 2 if it is a range forecast and 3 if it is a point forecast.	*GUIDE_S*
Supporting Information	Measured as the number of management forecast for the same quarter on measures other than earnings per share.	*SUPPORT*
SFAS 142	Dummy variable equal to one for all observations after the implementation of SFAS 142 and zero otherwise.	*SFAS*142
Treated Firms	Dummy variable equal to one if the firm was the acquiror in at least one M&A deal before and after SFAS 142, or at least one M&A deal before SFAS 142, and zero otherwise. We consider completed M&A deals in which at least 90% of the outstanding shares were acquired.	*TREATED*
Earnings Surprise	Is defined as the difference between actual EPS (from I/B/E/S) and the most recent analyst estimate before earnings announcement	*SURPRISE*

Figure 1: Analyst Reaction to Management Forecasts

Figure 1.1: Analyst Forecast Correction Towards Guidance

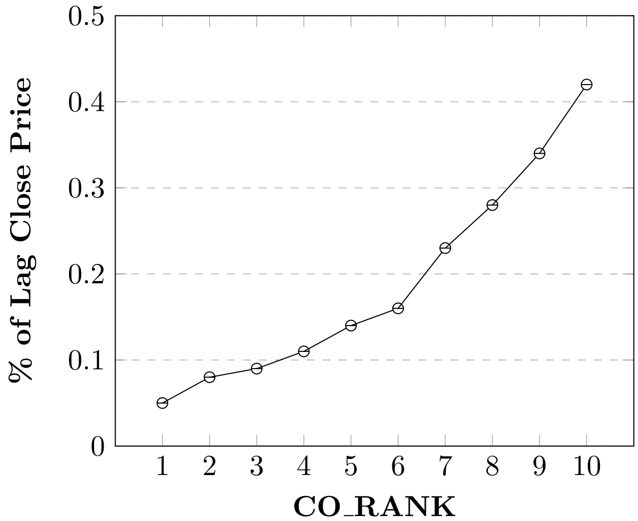

Figure 1.2: Change in Analyst Forecast Error After Guidance

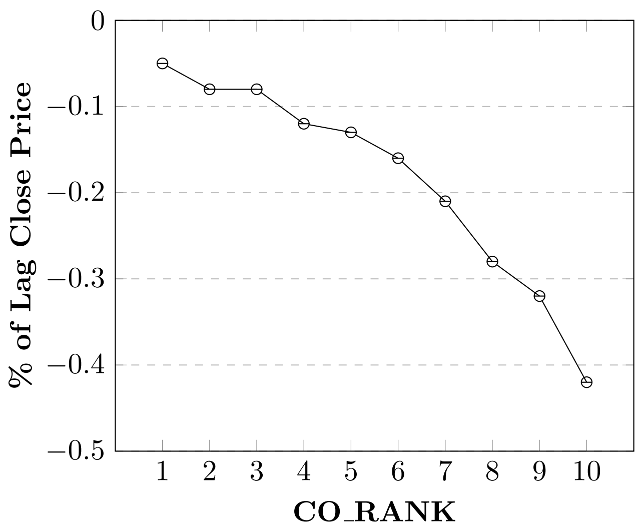

Figure 2: Market Reaction to Management Forecasts

-Cumulative Abnormal Returns-

Figure 2.1: Market Reaction to Good News Guidance

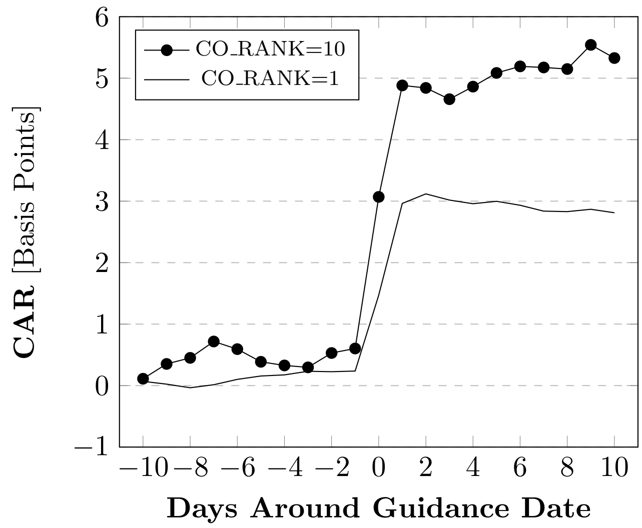

Figure 2.2: Market Reaction to Bad News Guidance

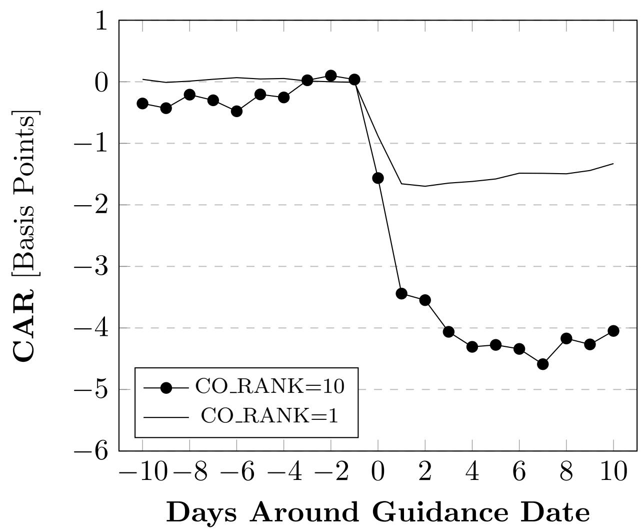

Figure 3: Shock to Conditional Conservatism

-Implementation of SFAS 142-

Figure 3.1: Change in Conditional Conservatism

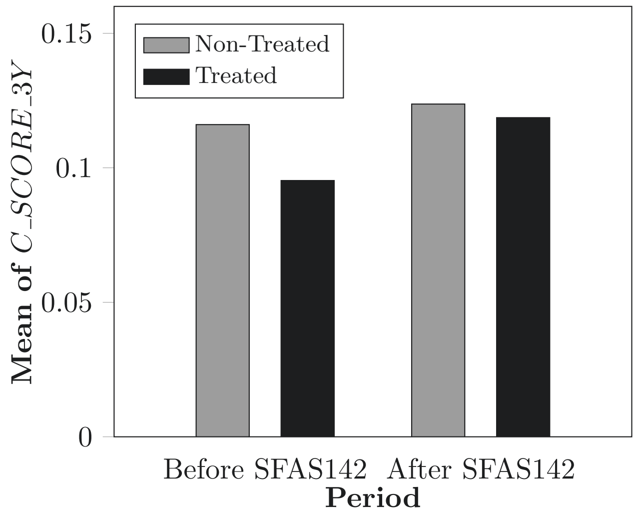

Figure 3.2: Parallel Trends I

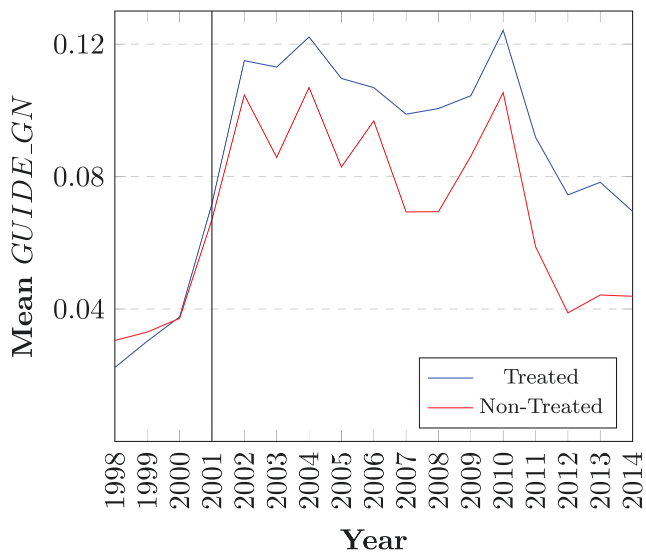

Figure 3.3: Parallel Trends II

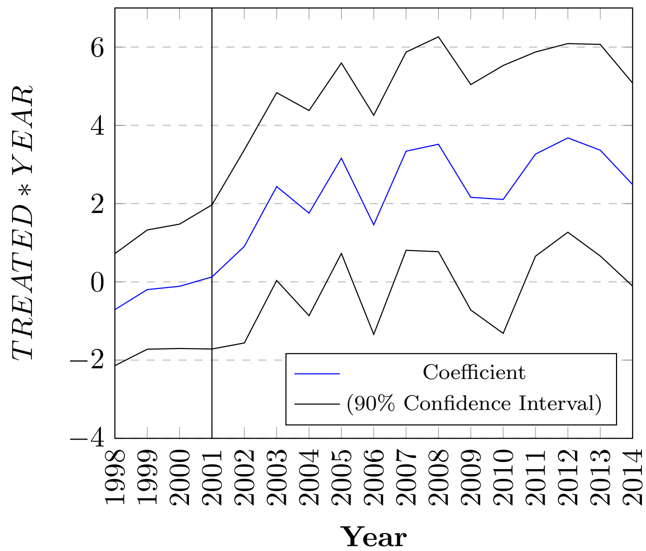

Table 1

Descriptive Statistics

Panel A: Sample Distribution by Year and Conservatism Rank

Year	Conditional Conservatism Rank										Total
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
1997	421	402	410	406	402	400	407	413	410	398	4,069
1998	485	482	482	482	481	482	481	483	479	476	4,813
1999	529	527	526	526	523	522	518	525	520	525	5,241
2000	538	540	539	536	538	540	529	534	541	529	5,364
2001	546	541	546	543	543	540	544	543	549	541	5,436
2002	561	559	559	557	561	558	557	559	558	550	5,579
2003	602	597	596	599	599	593	591	597	600	599	5,973
2004	603	607	604	603	606	605	607	605	606	602	6,048
2005	599	593	591	596	593	599	594	602	596	597	5,960
2006	573	574	569	570	572	564	570	565	572	571	5,700
2007	550	550	546	549	547	547	548	547	548	548	5,480
2008	501	504	502	499	503	502	504	505	502	502	5,024
2009	515	517	518	517	514	517	518	517	516	516	5,165
2010	518	513	511	516	514	516	515	517	513	513	5,146
2011	499	498	498	501	495	501	496	497	498	497	4,980
2012	488	482	483	484	482	485	487	485	484	482	4,842
2013	481	482	482	481	485	482	480	482	484	479	4,818
2014	451	450	451	448	450	450	448	449	450	449	4,496
Total	**9,460**	**9,418**	**9,413**	**9,413**	**9,408**	**9,403**	**9,394**	**9,425**	**9,426**	**9,374**	**94,134**

Table 1 (cont'd)

Panel B: Distribution of Firms and Management Forecast by Year

Year	Firms	Guiding Firms	% of Guiding Firms	# of Forecast	% of Good News	% of Bad News
1997	1,157	295	25.50%	384	19.27%	79.69%
1998	1,392	513	36.85%	711	16.46%	81.15%
1999	1,513	530	35.03%	741	22.67%	74.90%
2000	1,562	719	46.03%	1,111	19.26%	79.48%
2001	1,567	869	55.46%	1,820	21.92%	76.43%
2002	1,636	848	51.83%	1,848	33.71%	65.10%
2003	1,670	827	49.52%	1,987	33.17%	66.33%
2004	1,684	844	50.12%	2,187	34.16%	65.16%
2005	1,638	751	45.85%	2,002	34.12%	65.23%
2006	1,588	704	44.33%	1,887	33.55%	65.87%
2007	1,501	625	41.64%	1,738	29.75%	69.91%
2008	1,384	555	40.10%	1,574	32.40%	67.41%
2009	1,399	492	35.17%	1,420	39.65%	60.14%
2010	1,378	492	35.70%	1,508	41.38%	58.49%
2011	1,327	486	36.62%	1,439	30.92%	68.94%
2012	1,293	491	37.97%	1,425	27.44%	72.42%
2013	1,285	483	37.59%	1,415	25.65%	74.20%
2014	1,267	487	38.44%	1,344	24.93%	75.07%
Total	**3,056**	**2,423**	**79.29%**	**26,541**	**30.39%**	**68.96%**

Table 1 (cont'd)

Panel C: Distribution of Firms by Number of Management Forecast Issued

# of Forecast	All Forecasts	Good News	Bad News
0	633	1,489	779
1	470	479	489
2-5	772	589	807
6-10	382	259	387
11+	799	240	594
Total	**3,056**	**3,056**	**3,056**

Panel D: Distribution of Management Forecasts per Firm by News Type

# of Forecast	Mean	Median	Std. Dev.	Min	Max
All	13.13	6.00	15.41	0.00	64.00
Good News	4.04	1.00	5.87	0.00	39.00
Bad News	9.00	5.00	10.46	0.00	50.00

Panel E: Distribution of Management Forecasts by Conservatism Rank

CO_RANK	# of Forecast	% of Good News	% of Bad News
1	3,330	31.95%	67.54%
2	3,491	30.97%	68.55%
3	3,309	32.64%	66.76%
4	3,214	31.24%	68.20%
5	3,062	31.58%	67.86%
6	2,802	28.41%	70.56%
7	2,609	28.48%	70.64%
8	2,166	28.86%	70.50%
9	1,646	28.68%	70.72%
10	912	25.55%	73.46%
Total	**26,541**	**30.39%**	**68.96%**

Table 1 (cont'd)

Panel F: Summary Statistics

	Mean	Std. Dev.	1%	25%	Median	75%	99%
Management Forecast Variables							
$GUIDE$	0.282	0.450	0.000	0.000	0.000	1.000	1.000
$GUIDE\_GN$	0.086	0.280	0.000	0.000	0.000	0.000	1.000
$GUIDE\_BN$	0.194	0.396	0.000	0.000	0.000	0.000	1.000
MF_REG_GN	0.335	0.756	0.000	0.000	0.000	0.000	3.000
MF_REG_BN	0.754	1.163	0.000	0.000	0.000	1.000	4.000
N_SIZE	0.061	0.101	0.000	0.010	0.026	0.070	0.551
Analyst and Market Reaction Variables							
AF_CORR	0.146	0.399	-0.390	0.000	0.026	0.134	2.330
ΔAF_ERROR	-0.130	0.398	-2.276	-0.118	-0.018	0.000	0.445
DIS_AFTER	0.045	0.069	0.000	0.011	0.023	0.048	0.381
CAR	-0.926	10.357	-33.040	-5.515	-0.325	4.658	23.695
Conditional Conservatism Variables							
C_SCORE	0.117	0.135	-0.255	0.044	0.115	0.187	0.519
G_SCORE	0.004	0.038	-0.097	-0.015	0.007	0.023	0.119
CO	0.121	0.124	-0.256	0.065	0.121	0.178	0.499
C_SCORE_3y	0.112	0.113	-0.187	0.044	0.113	0.180	0.392
CO_RANK	5.496	2.873	1.000	3.000	5.000	8.000	10.000

Table 1 (cont'd)

Panel F: (cont'd) Summary Statistics

	Mean	Std. Dev.	1%	25%	Median	75%	99%
Control Variables							
SIZE	5.008	1.787	0.999	3.752	4.979	6.234	9.066
BTM	0.571	0.403	0.069	0.290	0.469	0.734	2.221
LEV	0.179	0.167	0.000	0.009	0.155	0.294	0.636
ROA	0.007	0.051	-0.157	0.002	0.012	0.023	0.075
AF	1.517	1.013	0.000	0.693	1.609	2.303	3.296
INST	0.487	0.347	0.000	0.114	0.551	0.789	1.076
DIS	2.279	3.916	0.000	0.000	1.000	3.000	23.000
S_EARN	32.895	75.224	0.282	2.546	7.202	24.325	479.569
S_CFO	1.395	3.940	0.026	0.080	0.241	0.892	23.746
RET_VOL	3.164	1.490	1.059	2.086	2.817	3.899	8.197
BID_ASK	0.991	1.529	0.018	0.106	0.305	1.227	7.875
FE_BEFORE	0.006	0.014	0.000	0.001	0.002	0.005	0.080
AB_ACC	0.017	0.095	-0.287	-0.025	0.005	0.044	0.382
RET	0.035	0.321	-0.555	-0.116	0.017	0.153	0.931
FD	0.268	0.362	0.000	0.003	0.041	0.515	0.999
LIT	0.387	0.487	0.000	0.000	0.000	1.000	1.000
INSIDE	0.026	6.245	-5.635	0.000	0.000	0.000	6.023
HHI	0.245	0.189	0.048	0.115	0.187	0.308	0.963
ACCURACY	0.004	0.009	0.000	0.001	0.002	0.004	0.049
BINDEP	0.881	0.166	0.333	0.800	1.000	1.000	1.000
AUDIT_FE	0.471	0.267	0.143	0.250	0.333	0.667	1.000
GUIDE_H	2.228	1.016	0.000	2.000	3.000	3.000	3.000
GUIDE_S	2.092	0.444	1.000	2.000	2.000	2.000	3.000
SUPPORT	1.101	0.992	0.000	0.000	1.000	2.000	4.000

Table 1 (cont'd)

Panel G: Mean Values of Selected Variables by Conservatism Rank

Decile	1-2	3-4	5-6	7-8	9-10	t-test (1-2)-(9-10)	t-stat	Rank Correlation
Situational Incentives								
FD	0.256	0.245	0.242	0.268	0.315	-0.058	-15.33	-0.003
LIT	0.413	0.366	0.382	0.409	0.365	0.049	9.72	-0.0184
INSIDE	-0.025	-0.083	-0.088	0.125	0.201	-0.226	-3.78	0.0765
HHI	0.249	0.230	0.243	0.248	0.256	-0.007	-3.21	0.0264
Management Credibility								
ACCURACY	0.062	0.074	0.088	0.110	0.071	-0.009	-2.35	-0.1443
Internal and External Assurance								
BINDEP	0.826	0.853	0.866	0.880	0.861	-0.035	-16.28	0.1049
AUDIT_FE	0.344	0.326	0.308	0.277	0.240	0.104	33.22	-0.0914
INST	0.555	0.578	0.539	0.460	0.302	0.253	80.17	-0.252
Guidance Characteristics								
GUIDE_H	2.398	2.304	2.195	2.097	1.904	0.494	21.13	-0.1673
GUIDE_S	2.123	2.109	2.082	2.068	2.031	0.092	8.51	-0.0651
SUPPORT	0.960	1.055	1.179	1.230	1.126	-0.166	-9.00	0.079
Other								
SIZE	6.939	5.652	4.853	4.114	3.472	3.467	252.43	-0.6915
BTM	0.348	0.451	0.533	0.645	0.880	-0.532	-130.00	0.4691
LEV	0.199	0.182	0.159	0.154	0.201	-0.001	-0.60	-0.0609
ROA	0.017	0.013	0.008	0.001	-0.004	0.022	39.15	-0.3138
AF	2.515	2.006	1.547	1.075	0.439	2.077	318.42	-0.725
FE_BEFORE	0.003	0.004	0.006	0.009	0.015	-0.012	-35.59	0.3759
AB_ACC	0.010	0.008	0.006	0.005	0.003	0.007	11.00	-0.0121

The sample consist of 94,134 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99%. See Appendix B for variable definitions.

Table 2

Conditional Conservatism Commitment and Management Forecasts Frequency

	(1) $GUIDE\_GN$	(2) $GUIDE\_BN$	(3) MF_REG_GN	(4) MF_REG_BN
CO_RANK_{t-4}	0.242**	-0.602***	0.988**	-1.834***
	(0.104)	(0.175)	(0.419)	(0.698)
LEV_{t-4}	-1.565	-1.445	-6.929	-3.565
	(1.196)	(2.057)	(5.046)	(8.350)
$SIZE_{t-4}$	0.983***	2.403***	4.591***	15.056***
	(0.195)	(0.351)	(0.892)	(1.560)
BTM_{t-4}	0.694*	-3.093***	-0.245	-6.952***
	(0.395)	(0.633)	(1.435)	(2.356)
ROA_{t-4}	-5.641***	14.359***	-18.837***	37.958***
	(2.147)	(3.004)	(5.819)	(10.759)
AF_{t-4}	1.370***	3.532***	3.710***	15.042***
	(0.261)	(0.416)	(0.986)	(1.603)
$INST_{t-4}$	2.361***	4.739***	7.049**	17.939***
	(0.850)	(1.490)	(3.571)	(6.171)
S_EARN_{t-4}	-0.006*	-0.012**	-0.022	-0.040*
	(0.003)	(0.006)	(0.014)	(0.024)
DIS_{t-4}	-0.321***	-0.483***	-1.152***	-1.984***
	(0.032)	(0.050)	(0.114)	(0.177)
RET_VOL_{t-4}	-0.224*	-1.296***	-1.528***	-5.175***
	(0.117)	(0.201)	(0.450)	(0.762)
BID_ASK_{t-4}	0.294***	0.638***	1.107***	2.056***
	(0.100)	(0.175)	(0.368)	(0.656)
AB_ACC_{t-4}	-3.427*	6.528***	-1.869	20.562***
	(1.773)	(2.221)	(3.422)	(4.750)
$BINDEP_{t-4}$	0.642	-1.024	2.426	-4.341
	(1.007)	(1.762)	(4.214)	(7.136)
Observations	94,134	94,134	94,134	94,134
Number of Firms	3,056	3,056	3,056	3,056
Time F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm
R^2	0.105	0.192	0.309	0.387

The estimated model is: $MF_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. See Appendix B for variable definitions. The sample consist of 94,134 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 3

The Effect of Future Stock Returns on the Association Between Conditional Conservatism and Management Forecasts Frequency

	(1) $GUIDE\_GN$	(2) $GUIDE\_BN$
CO_RANK_{t-4}	0.207*	-0.530***
	(0.108)	(0.178)
RET_{t+1}	-1.507**	-1.178
	(0.679)	(0.982)
$RET_{t+1} * CO\_RANK_{t-4}$	0.202**	-0.073
	(0.087)	(0.150)
Control Variables	Yes	Yes
Observations	89,588	89,588
Number of Firms	3,008	3,008
Time F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Cluster S.E.	Firm	Firm
R^2	0.107	0.191

The estimated model is: $MF_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * RET_{t+1} + \beta_3 * RET_{t+1}\gamma * Controls_{t-4} + \epsilon_t$. See Appendix B for variable definitions. The full-sample consist of 94,134 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 4

Analysts and Market Reaction to Management Forecasts

Panel A: Good News Management Forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	AF_CORR		ΔAF_ERROR		DIS_AFTER		CAR	
CO_RANK_{t-4}	0.000	-0.007**	-0.003	0.007*	-0.001	0.000	0.005	0.093
	(0.003)	(0.003)	(0.003)	(0.004)	(0.000)	(0.001)	(0.062)	(0.119)
N_SIZE	0.193	0.227	-0.791***	-0.798***	0.489***	0.478***	8.925*	9.175*
	(0.282)	(0.283)	(0.290)	(0.288)	(0.075)	(0.073)	(5.054)	(5.073)
$N\_SIZE * CO\_RANK_{t-4}$	0.338***	0.327***	-0.259***	-0.234***	-0.027**	-0.029**	3.124***	3.519***
	(0.068)	(0.068)	(0.065)	(0.065)	(0.012)	(0.012)	(1.089)	(1.080)
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7,800	7,650	7,786	7,650	7,567	7,421	7,502	7,354
Number of Firms	1,513	1,497	1,511	1,497	1,453	1,437	1,466	1,447
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.524	0.521	0.546	0.574	0.579	0.564	0.0281	0.0118

Panel B: Bad News Management Forecast

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	AF_CORR		ΔAF_ERROR		DIS_AFTER		CAR	
CO_RANK_{t-4}	0.006**	-0.020***	-0.003	0.019***	-0.002***	-0.002***	-0.009	0.396***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.000)	(0.001)	(0.057)	(0.095)
N_SIZE	0.961***	1.015***	-0.900***	-0.918***	0.361***	0.355***	-19.312***	-18.348***
	(0.214)	(0.205)	(0.226)	(0.219)	(0.028)	(0.027)	(2.338)	(2.194)
$N\_SIZE * CO\_RANK_{t-4}$	0.228***	0.195***	-0.177***	-0.150***	-0.004	-0.006	-0.593	-0.318
	(0.042)	(0.041)	(0.046)	(0.045)	(0.006)	(0.005)	(0.440)	(0.406)
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	16,644	16,314	16,613	16,314	16,171	15,866	16,062	15,700
Number of Firms	2,031	2,008	2,027	2,008	1,946	1,929	1,953	1,936
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.438	0.444	0.396	0.381	0.380	0.355	0.134	0.107

The estimated model is: $Y_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * N\_SIZE + \beta_3 * N\_SIZE * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. Y_t is equal to AF_CORR, ΔAF_ERROR, DIS_AFTER, and CAR. Panel A presents the results for good news management forecasts, while panel B presents the results for bad news management forecasts. See Appendix B for variable definitions. The sample consist of 26,541 firm-quarter guiding observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses, and the model includes industry and time fixed effects.

Table 5

Exogenous Change in Conditional Conservatism

-FASB Statement No.142-

Panel A: Management Forecast Frequency and Analysts/Market Reactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable	$GUIDE\_GN$	$GUIDE\_BN$	AF_CORR		ΔAF_ERROR		DIS_AFTER		CAR	
			Good News	Bad News	Good News	Bad News	Good News	Bad News	Good News	Bad News
$TREATED$	-1.181**	0.533	-0.031	0.019	0.048	-0.001	-0.021**	-0.002	-0.911	-0.715
	(0.495)	(0.833)	(0.039)	(0.032)	(0.041)	(0.032)	(0.009)	(0.006)	(1.236)	(0.939)
$SFAS142$	-1.644*	-3.682**	0.051	0.113*	0.040	-0.081	-0.109***	0.047***	3.030	7.707*
	(0.988)	(1.510)	(0.048)	(0.062)	(0.056)	(0.096)	(0.025)	(0.010)	(3.130)	(4.494)
$TREATED * SFAS142$	2.269**	2.079	-0.006	-0.029	-0.013	0.015	0.012*	-0.009	0.122	0.782
	(0.888)	(1.386)	(0.028)	(0.029)	(0.031)	(0.032)	(0.007)	(0.006)	(1.321)	(0.985)
N_SIZE	-	-	0.776***	1.599***	-1.079***	-1.375***	0.325***	0.321***	15.018**	-19.015***
	-	-	(0.224)	(0.152)	(0.225)	(0.152)	(0.054)	(0.022)	(6.046)	(2.303)
$N\_SIZE * TREATED * SFAS142$	-	-	1.148***	0.534**	-0.948**	-0.316	0.001	-0.004	11.079*	-0.154
	-	-	(0.379)	(0.207)	(0.388)	(0.220)	(0.070)	(0.028)	(6.716)	(3.101)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yesd
Observations	65,516	65,516	4,478	9,875	4,478	9,875	4,392	9,732	4,316	9,554
Number of Firms	1,684	1,684	808	1,106	808	1,106	784	1,072	776	1,062
Time & Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.0254	0.108	0.582	0.434	0.659	0.363	0.605	0.382	0.0837	0.193

The estimated model in Panels A and C columns (1) to (2)is: $MF_t = \beta_0 + \beta_1 * TREATED + \beta_2 * SFAS142 + \beta_3 * TREATED * SFAS142 + \gamma * Controls_{t-4} + \epsilon_t$. MF_t is alternatively $GUIDE\_GN$, and $GUIDE\_BN$. The estimated model in Panels A and C columns (2) to (10) is: $Y_t = \beta_0 + \beta_1 * TREATED + \beta_2 * SFAS142 + \beta_3 * TREATED * SFAS142 + \beta_4 * N\_SIZE + \beta_5 * N\_SIZE * TREATED * SFAS142 + \gamma * Controls_t + \epsilon_t$. Y_t alternatively AF_CORR , ΔAF_ERROR, DIS_AFTER, and CAR. See Appendix B for variable definitions. The sample consist of 94,134 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses. Both models include time and industry fixed effects.

Table 5 (cont'd)

Panel B: Balance Properties Propensity SCORE Matching

Variable	**Unmatched / Matched**	**Mean Treated**	**Mean Control**	**% bias**	**% Dec. bias**	**t-test t**	**t-test p>t**	**V(T)/V(C)**
SIZE	U	4.9889	4.491	27.4	96.1	49.07	0.000	0.91
	M	4.6435	4.6241	1.1		1.61	0.108	0.88
ROA	U	0.00713	0.00388	5.6	96.6	10.19	0.000	0.79
	M	0.00498	0.00487	0.2		0.30	0.764	0.70
LEV	U	0.16311	0.12498	24.4	95.5	43.38	0.000	1.04
	M	0.13268	0.13439	-1.1		-1.66	0.096	0.91
AF	U	6.5009	6.3347	2.7	66.1	4.77	0.000	0.95
	M	6.3907	6.447	-0.9		-1.34	0.181	0.96
BTM	U	0.55882	0.5564	0.6	-84.3	1.07	0.285	0.86
	M	0.56562	0.56115	1.1		1.63	0.103	0.86

Sample	**Ps R2**	**LR chi2**	**p > chi2**	**Mean bias**	**Med bias**	**B**	**R**	**% Conc.**	**% Bad**
Unmatched	0.022	3983.34	0.000	12.1	5.6	35.6	0.91	20	0
Matched	0.000	20.04	0.001	0.9	1.1	3.0	0.87	20	0

Table 6

Market Reactions to Good News Management Forecasts

Non-Crisis vs. Credibility Crisis Periods

	(1)	(2)	(3)	(4)
	Non-Crisis Period	Enron/Worldcom Period	Financial Crisis Period	Crisis Periods
CO_RANK_{t-4}	0.141	0.356	-0.779	-0.069
	(0.134)	(0.371)	(0.868)	(0.331)
N_SIZE	10.879**	0.475	-36.522†	-5.644
	(5.058)	(15.332)	(23.489)	(12.730)
$N\_SIZE * CO\_RANK_{t-4}$	2.969**	7.748**	12.494*	8.860***
	(1.186)	(3.813)	(6.718)	(3.181)
Control Variables	Yes	Yes	Yes	Yes
Observations	6,042	710	295	1,005
Number of Firms	1,284	436	218	583
Time F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm
R^2	0.058	0.104	0.235	0.092

The estimated model is: $Y_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * N\_SIZE + \beta_3 * N\_SIZE * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. See Appendix B for variable definitions. Enron/Worldcom period include observations from Q4 2001 to Q1 2003, financial crisis period include observations from Q3 2008 to Q1 2009 and Crisis periods combine both. The guiding sample consist of 26,541 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, *, indicate significance at the 1%, 5% and 10%. † indicate significance at the 10% for one-tailed test. Robust standard errors in parentheses.

Table 7

The Effect of the Information Environment on the Relation Between Conditional Conservatism and Management Forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dependent Variable		$GUIDE\_GN$			AF_CORR			ΔAF_ERROR			DIS_AFTER			CAR	
Aggregate Measure	Low	Med	High	Low	Med	High	Low	Med	High	Low	Med	High	Low	Med	High
CO_RANK_{t-4}	-0.100	0.307†	0.337**	-0.005*	-0.011***	-0.004	0.003	0.006	0.006	0.001	0.000	0.000	-0.049	0.204	0.236
	(0.227)	(0.205)	(0.161)	(0.003)	(0.004)	(0.010)	(0.002)	(0.006)	(0.011)	(0.001)	(0.001)	(0.001)	(0.165)	(0.188)	(0.287)
N_SIZE	-	-	-	0.752***	0.328	-0.366	-0.615**	-0.868**	-0.547	0.508***	0.414***	0.564***	8.611	-1.304	2.224
	-	-	-	(0.220)	(0.332)	(0.858)	(0.255)	(0.368)	(0.750)	(0.099)	(0.112)	(0.135)	(6.162)	(8.474)	(11.711)
$N\_SIZE * CO\_RANK_{t-4}$	-	-	-	0.103	0.251***	0.561***	-0.121*	-0.156*	-0.386***	-0.046**	-0.012	-0.044**	3.396**	5.887***	5.605**
	-	-	-	(0.065)	(0.078)	(0.159)	(0.067)	(0.088)	(0.144)	(0.020)	(0.019)	(0.021)	(1.617)	(1.932)	(2.443)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,233	23,685	22,630	2,852	2,513	1,712	2,852	2,513	1,712	2,850	2,511	1,701	2,772	2,445	1,612
Number of Firms	1,373	1,985	2,160	624	769	672	624	769	672	623	769	668	614	755	634
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.056	0.041	0.030	0.383	0.272	0.260	0.417	0.315	0.335	0.424	0.386	0.454	0.100	0.096	0.125

The estimated model in columns (1) to (3) is: $MF_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. In columns (4) to (15) the estimated model is: $Y_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * N\_SIZE + \beta_3 * N\_SIZE * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. Low/Med/High samples include firms in the bottom/med/top tercile of IA. See Appendix B for variable definitions. The full sample consist of 94,134 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.† indicate significance at the 10% for one-tailed test. Robust standard errors in parentheses.

Table 8

Controlling for Bundled Forecast Effects on the Relation Between Conditional Conservatism and Management Forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Rogers and Van Buskirk (2013) Approach					**Traditional Approach (Non-Bundled Forecasts)**				
	$GUIDE\_GN$	AF_CORR	ΔAF_ERROR	DIS_AFTER	CAR	$GUIDE\_GN$	AF_CORR	ΔAF_ERROR	DIS_AFTER	CAR
CO_RANK_{t-4}	0.252***	-0.007*	0.008*	-0.002*	0.017	0.155*	-0.003	-0.001	0.001	-0.180
	(0.090)	(0.004)	(0.005)	(0.001)	(0.151)	(0.093)	(0.007)	(0.009)	(0.002)	(0.280)
N_SIZE	-	-0.162	0.068	0.059	-3.763	-	0.342	-1.310***	0.593***	9.395
	-	(0.141)	(0.127)	(0.041)	(2.359)	-	(0.377)	(0.436)	(0.102)	(7.492)
$N\_SIZE * CO\_RANK_{t-4}$	-	0.195***	-0.148***	0.009	1.505*	-	0.274***	-0.069	-0.033*	3.222*
	-	(0.065)	(0.054)	(0.009)	(0.821)	-	(0.096)	(0.111)	(0.019)	(1.913)
$SURPRISE_t$	-	0.300***	-0.306***	0.024	4.640**	-	-	-	-	-
	-	(0.092)	(0.091)	(0.021)	(2.074)	-	-	-	-	-
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,134	4,735	4,735	4,663	4,545	94,134	1,618	1,618	1,588	1,506
Number of Firms	3,056	1,308	1,308	1,283	1,264	3,056	813	813	796	766
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.042	0.154	0.271	0.293	0.045	0.047	0.219	0.389	0.501	0.110

The estimated model for columns (1) and (6) is: $MF_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. The estimated model for columns (2) to (5) and (7) to (10) is: $Y_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * N\_SIZE + \beta_3 * N\_SIZE * CO\_RANK_{t-n} + \beta_3 * SURPRISE_t + \gamma * Controls_{t-4} + \epsilon_t$. See Appendix B for variable definitions. The full sample consists of 94,134 firm-quarter observations, the sample of guiding firms consist of 26,541 firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 9

Market Reaction to Earnings Announcement

Dependent Variable: Cumulative Abnormal Returns

	(1)	(2)
	Good News	Bad News
CO_RANK_{t-4}	-0.231**	-0.021
	(0.102)	(0.075)
$SURPRISE$	8.934***	7.036***
	(1.607)	(0.875)
Control Variables	Yes	Yes
Observations	6,842	14,141
Number of Firms	1,327	1,722
Time F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Cluster S.E.	Firm	Firm
R^2	0.040	0.029

The estimated model is: $EA\_CAR_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * SURPRISE_t + \gamma * Controls_{t-4} + \epsilon_t$. EA_CAR measure cumulative abnormal returns over a 3 day window around the earnings announcement date, and are estimated using the market model. $SURPRISE$ is the earnings surprise measured as the difference between actual earnings and analysts earnings consensus estimate before quarter end. See Appendix B for variable definitions. The guiding sample consist of 26,541 guiding firm-quarter observations for the period 1997-2014. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Robust standard errors in parentheses.

Table 10

Managerial Overconfidence

	(1) $GUIDE\_GN$	(2) $GUIDE\_BN$	(3) AF_CORR	(4) ΔAF_ERROR	(5) DIS_AFTER	(6) CAR
CO_RANK_{t-4}	0.397**	-0.805***	-0.002	0.003	-0.000	0.011
	(0.189)	(0.300)	(0.004)	(0.004)	(0.001)	(0.144)
$OVER$	0.660	-0.753	-0.009†	0.012†	0.003	0.019
	(0.585)	(0.958)	(0.007)	(0.008)	(0.002)	(0.284)
N_SIZE	-	-	0.147	-0.457	0.448***	6.597
	-	-	(0.251)	(0.316)	(0.088)	(5.121)
$N\_SIZE * CO\_RANK_{t-4}$	-	-	0.302***	-0.214**	-0.020	4.365***
	-	-	(0.068)	(0.087)	(0.016)	(1.330)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,869	41,869	4,455	4,455	4,404	4,283
Number of Firms	1,439	1,439	822	822	814	800
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.043	0.059	0.190	0.298	0.390	0.088

For columns (1) and (2) the estimated model is: $MF_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. MF_t is either $GUIDE\_GN$ or $GUIDE\_BN$. For columns (3) - (6), the estimated model is:$Y_t = \beta_0 + \beta_1 * CO\_RANK_{t-n} + \beta_2 * N\_SIZE + \beta_3 * N\_SIZE * CO\_RANK_{t-n} + \gamma * Controls_{t-4} + \epsilon_t$. Y_t is equal to AF_CORR, ΔAF_ERROR, DIS_AFTER, and CAR. Panel A columns (3) - (6) presents the results for good news management forecasts. See Appendix B for variable definitions. The sample consist of 41,869 firm-quarter observations for the period 1997-2014, which had the data available in ExecuComp to calculate $OVER$. Continuous variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.† indicate significance at the 10% for one-tailed test. Robust standard errors in parentheses, and the model includes firm and time fixed effects.

Chapter 3

Firms Reaction to Peers Non-Disclosure

3.1 Introduction

We study how an exogenous shock that decreases information disclosure affects peer firms. The information-transfer literature shows that the release of information about one firm can be relevant to its peers because they face similar economic conditions (Schipper, 1990). Information-transfer occurs when the information released by one firm (e.g. earnings announcements, restatements, or management earnings forecasts) produces an unexpected stock price correction for other firms with similar earnings determinants. Prior literature has extensively studied and documented information-transfer effects when new information about the firm is released to markets.[1] However, to the best of our knowledge, there is no prior work studying how peer firms react to a loss of information in the context of information-transfers.

Although not directly studying a setting where related firms limit information disclosure, of particular interest for our paper is the study by Kim et al. (2008) which suggests that information-transfers can be positive or negative. A negative information transfer arises when information released by a peer produces an unexpected reduction on related firms stock prices. In this situation, managers would have incentives to voluntarily disclose their private information to counteract the negative information-transfers from peers disclosures (Desir, 2012).[2] According to Kim et al. (2008), the sign

[1] See, Foster (1981); Olsen and Dietrich (1985); Baginski (1987); Pownall and Waymire (1989); Han et al. (1989); Han and Wild (1990); Freeman and Tse (1992); Han and Wild (1997); Laux et al. (1998); Thomas and Zhang (2008); Alves et al. (2009); Hilary and Shen (2013); Hope and Zhao (2017).

[2] Managers' decision to voluntary disclose their private information will depend on a rational assessment of the trade-offs between the costs (e.g. litigation risks, disclosure costs, proprietary costs) and benefits (e.g. increasing stock prices) associated with the disclosure (Healy and Palepu, 2001; Hirst et al., 2008). In the context of negative information-

of the information transfer (positive or negative) depends on the type of competitive relation between the firm and its peers (i.e. whether they are rival or non-rival firms).

Prior analytical work emphasizes this role of competition in driving voluntary disclosure, and suggests that managers voluntarily disclose their private information to differentiate their firms from competitors, or to respond to the disclosure made by them (see e.g. Verrecchia (1983); Dye (1985); Wagenhofer (1990); Suijs (1999)). Related literature also shows that information-transfers depend on the information environment, and that they are stronger for non-forecasting firms (Pownall and Waymire, 1989), and occur prior to the firms' own earnings announcement, and for firms with weak information environments (Graham and King, 1996). More recently, several studies show that managers disclose bad news in response to peers' disclosure of bad news (Tse and Tucker, 2009; Sletten, 2011), and that managers in more (less) concentrated industries are more likely to disclose good news after their rival firms announce good news (bad news) (Desir, 2012). The preceding argumentation indicates that managers may take a purposeful action (e.g. voluntary disclosure) to prevent negative information-transfers.

Following the same line of reasoning, we argue that peer firms are likely to change their disclosure behavior when there is less information on the market about a peer firm, and that this change in behavior will depend on whether these firms are rival or non-rival peers. In particular, we study how the adoption of inevitable disclosure doctrine (IDD) affects the disclosure of peer firms in those states *not* affected by the IDD.[3]

IDD adoption provides a clear setting in which to study whether firms intervene to affect the information-transfer process when there is a negative shock to the information environment (i.e., in our setting, less information). Li et al. (2018) show that the staggered adoption of IDD by U.S. state courts generates exogenous variation in the proprietary costs of disclosure, and that firms respond to IDD adoption by reducing the level of disclosure. In particular, they show that affected firms reduce disclosure on customers' identity. This type of proprietary information is particularly relevant, as disclosures regarding firm's customers may assist capital market participants in evaluating firm's current and future revenues, trading relationships, productive capacity, price/cost margins, etc. At the aggregate level, disclosure regarding firm's customers could help capital-market participants to better estimate information about the industry as a whole. Moreover, capital-markets participants

transfers, managers' incentives and shareholders' interest are aligned so that voluntary disclosure of private information is beneficial for both.

[3]The inevitable disclosure is a legal doctrine through which an employer can forbid an employee from working for another firm, claiming that in fulfilling the new role the employee will inevitably disclose firm's trade secrets. Klasa et al. (2018) argue that the staggered adoption of IDD exogenously increases proprietary costs of disclosure in the adopting states.

can potentially infer information about industry revenues from disclosures made by the customer firms (Ellis et al., 2012). Thus, lower levels of this type of proprietary information disclosure will result in valuable information vanishing from the market.

We expect that IDD adoption significantly influences the information environment for peer firms operating in non-IDD states. We argue that IDD adoption affects the information environment of peer firms in two main ways. First, lower levels of disclosure of firms located in those states affected by IDD adoption is expected to elicit information-transfers that may cause the disclosure behavior of peer firms located in states not affected by IDD adoption. Second, we expect peer firms' reaction (i.e., whether they increase or decrease voluntary disclosure as a reaction to the decrease in proprietary information by related firms) to depend on product-market competition at the industry level.

Prior literature suggests that the effect of competition on disclosure will depend on the source of competition, and that it is important to differentiate whether the competition comes from market size, product similarities, or entry costs (Lang and Sul, 2014). In the context of information-transfers, in more concentrated industries each firm's disclosure might provide more information about the industry as whole (Ali et al., 2014). For example, Desir (2012) argues that, in more concentrated industries, non-announcing firms will disclose more good news following peer good news ('me-too' story), while in less concentrated industries, non-announcing firms will disclose more good news following peer bad news ('not-me' story). Kim et al. (2008) argue that industry commonalities trigger positive information-transfers, whereas competitive shifts cause negative information-transfers. Therefore information-transfers will be negative (positive), depending on whether the peer is a rival (non-rival) firm announcing good or bad news. For instance, a positive revenue forecast made by a particular firm may convey good news to its peers (i.e. positive information-transfer) if it is indicative of a better outlook for the industry, or may convey bad news (i.e. negative information-transfer) if an increase in the firm's future revenue means that its peers lost market share (Kim et al., 2008).

Lower levels of disclosure by firms in IDD adopting states means that capital-market participants have less information to evaluate the industry as a whole. Therefore, we expect firms in non-IDD states to voluntary disclose (i.e. customer identity) more after IDD adoption, to compensate for the loss of positive information-transfers. Skeptical investors might also interpret lower levels of disclosure by firms in IDD adopting states as firms withholding bad news. In which case, we also expect firms to voluntary disclose more to counteract potential negative information-transfers. Alternatively, managers of peer firms in non-IDD states may not disclose their private information if they are uncertain about investors' response to disclosed information (Dye, 1998; Dutta and Trueman, 2002; Suijs, 2007). Ultimately, it is an empirical question whether firms in non-IDD states respond to less voluntary disclosure of peers in IDD adopting states.

We test our predictions using a large sample of US publicly-listed firms over the period 1994-2010. In our main research design we employ a difference-in-differences (DID) approach, based on the staggered adoption of IDD across U.S. states as plausible exogenous shock to proprietary costs of disclosure (Klasa et al., 2018; Li et al., 2018). We include year, state, and firm fixed-effects to control for economic trends, and time-invariant unobservable state and firm characteristics. Following Li et al. (2018), we proxy voluntary disclosure by firms disclosure choice of customer identity, and we measure it as the proportion of unidentified customers in Compustat Segment Files. We follow Desir (2012) in additional analysis and focus on whether the firms in IDD adopting states are industry leaders to maximize the power of our tests. Following Bloomfield (2018), we use different proxies of product-market competition, in an attempt to capture the different sources of competition. Our first measure is based on Kedia (2006) who classifies firms as facing strategic complement (substitutes) interactions when the slope of the firm's reaction function is positive (negative). The second measure captures the importance of capacity constraints in competition (Maggi, 1996). Firms in industries with more production flexibility (i.e. less capacity constraints) are more likely to engage in a Bertrand type of competition, while firms with less production flexibility (i.e. more capacity constraints) are more likely to engage in a Cournot type of competition. The third measure captures firms efforts to differentiate their products from their competitors.

Our results indicate that firms headquartered in non-IDD states, whose closest peer is a firm headquartered in IDD adopting states, respond to IDD adoption disclosing more information on customer identity. Moreover, the response is stronger, in magnitude and significance, when they the closest peer is an industry leader. We also, find results indicating that peer firms' reaction to IDD adoption is larger for firms facing strategic complement interactions, and for firms in industries with low production flexibility.

The paper continues as follows. Section 2 provides a brief review of the literature and sets our main hypotheses. Section 3 describes the research design. Section 4 discusses the sample and main results. Finally, section 5 offers the summary and conclusions of our study.

3.2 Prior Literature on Peer Effects and Main Prediction

Prior work shows that firm's disclosure decisions affects peer firms, both in terms of their stock prices and their disclosure choices. As noted in Matsumoto and Shaikh (2017), there are two main literatures on this issue. The first one is the information transfer literature, which shows that the release of firm information, such as earnings and management earnings forecasts affects related firms' stock prices (Foster, 1981; Han et al., 1989). This literature builds on the idea that peer firms are subject to similar economic forces, such as macro-economic shocks, or common demand/supply shocks. This means that the cash flows of peer firms are correlated, and therefore, disclosures from one firm provide information on the other firm's cash flows. More recently, a number of studies document that stock price reactions may respond not to a numerator (cash flow) effect, but rather, to a denominator effect, i.e., to information risk (e.g., Shroff et al. (2017)).

The second literature on this topic focuses on how peer firms disclosure decisions affects the disclosure choices of related firms. This literature presents mixed views and findings, and suggests that the effect of firm disclosures on its peers can be both complementary: where the disclosure decision of one firm encourages related firms' disclosure decisions (e.g., Tse and Tucker (2009)) and substitutive: where increases (decreases) in disclosure of one firm lower (increase) the disclosure of its peers (e.g., Baginski and Hinson (2016); Breuer et al. (2018)).

We attempt to disentangle the mixed findings in prior literature by identifying a source of exogenous variation in firm information disclosure and studying the effects of competition on disclosure. Following Kim et al. (2008), we expect that disclosure effects will depend on the source of competition, that is, whether the competition comes from market size, product similarities, or entry costs (Lang and Sul, 2014). According to the information-transfer literature, in concentrated industries, each firm's disclosure provides more information about the industry as a whole (Ali et al., 2014). For example, Desir (2012) argue that, in more concentrated industries, non-announcing firms disclose more good news following peers' good news ('mee-too' story), while in less concentrated industries, non-announcing firms disclose more good news following peers' bad news. Kim et al. (2008) argue that industry commonalities trigger positive information-transfers, whereas competitive shifts cause negative information-transfers. Therefore, we expect that information-transfers depend on whether the peer is a rival (non-rival) firm announcing good or bad news.

Lower levels of disclosure by firms means that capital-market participants have less information to evaluate the industry as a whole. Therefore, we expect non-rival firms to voluntary disclose more (i.e. customer information) after related firms stop disclosing information, to compensate for the loss of positive information-transfers. Skeptical investors might also interpret lower levels of disclosure as firms withholding bad news. In which case, we also expect non-rival firms to voluntary disclose more to counteract potential negative information-transfers. On the contrary, since bad news from rivals imply potential positive information-transfers from their peers (i.e., there is no need to counteract negative information-transfers), and given that disclosure is costly, we expect rival firms to engage in less voluntary disclosure after the negative change in disclosure by the related firm. Alternatively, managers of peer firms (both rival and non-rivals) may not disclose their private information if they are uncertain about investors' response to disclosed information (Dye, 1998; Dutta and Trueman, 2002; Suijs, 2007).

Accordingly, our hypothesis can be summarized as follows:

H1: *Exogenous decreases in firm proprietary information affects peer firms information environment. Peer firms response is contingent on competition.*

3.3 Research Design

To test our predictions, we estimate the following difference-in-differences (DiD) model:

$$Y_{i,t} = \beta_0 + \beta_1 * PEER_{i,t} + \gamma * CONTROLS_{i,s,t-1} + \mu_i + \eta_s + \theta_t + \epsilon_{i,s,t} \tag{3.1}$$

Where:

$i = firm,$

$s = state\ of\ firm's\ headquarters,$

$t = year.$

The dependent variable in model (1) is a proxy for the voluntary disclosure of customer information. Our main proxies capture firms disclosure choices regarding customer identity, an important aspect of this is that customer identity exists. In this sense non-disclosure reflects a managerial choice, and not the absence of information to disclose. Following Li et al. (2018) we measure customer identity disclosure using two proxies. The first proxy, $RATIO\_1$, is the percentage of unidentified customers. The second proxy, $RATIO\_2$, is the sales-weighted percentage of unidentified customers. Then our dependent variable is either: $R1 = ln(1 + RATIO\_1)$, or $R2 = ln(1 + RATIO\_2)$, note that higher values of R1 and R2 indicate less disclosure of customer information. Regulation S-K demands firms to disclose the amount of sales to an identity of any major customer (i.e. comprise more than 10% of firm consolidated sales revenues) if losing the customer would have a material negative effect on the firm. However, disclosure of costumer information is generally voluntary in the sense that many firms report the existence but not the name of major customers (Ellis et al., 2012).[4]

[4]Following Li et al. (2018), we require firms to have at least one customer that represent 10% (or more) of firm's annual total sales.

Our main independent variable, $PEER$, captures how firms react to an exogenous decrease of available information from firms in the same industry. We follow prior literature and exploit the staggered adoption of inevitable disclosure doctrine (IDD) by U.S. state courts as a plausible exogenous shock to the proprietary costs of disclosure (Klasa et al., 2018; Li et al., 2018). In those states where IDD is adopted the employer can prevent a current or former employee to work for another company, if the employer can prove that the employee will *inevitably* disclose trade secrets to his new employer. Thus, IDD adoption prevents rival firms to obtain confidential information through "employees job switching" increasing proprietary costs of disclosure (i.e. the marginal value of disclosure to its rivals is higher). In addition, to be protected by IDD firm's trade secrets should not be available from other public sources (i.e. firms should not disclose their proprietary information).[5] Li et al. (2018) shows that IDD adoption decreases significantly the amount of customers' identity disclosure. The more disclosure on customers information of a particular firm, the better capital-market participants can evaluate firm's revenues, trading relationships, productive capacity, and also industry revenues (Ellis et al., 2012). Therefore, IDD adoption will affect the information environment of peer firms in non-IDD adopting states.

We follow Klasa et al. (2018) to identify IDD-adopting states and the year of adoption/rejection, and define $PEER$ as a indicator variable that takes value one for firms headquartered in non-IDD states whose closest peer is a firm headquartered in a state adopting IDD in year t. To identify the closest peer of each firm we follow Hoberg and Phillips (2010) 'Text Network Industry Classification' (TNIC), and define the closest peer of a given firm as the firm with higher similarity in the 10-K business description based on the TNIC score devloped by Hoberg and Phillips (2010).[6]

Following prior literature, we introduce several controls in model (1), to capture potential determinants of voluntary disclosure. Following Li et al. (2018) we control for a firm's proprietary costs of disclosure including R&D (RD_EXP) and advertising expenditures (AD_EXP) relative to sales, and the proportion of intangible assets ($INTAN$). We also include an indicator variable taking value one when R&D expenditure is missing ($MISS\_RD$), as in Li et al. (2018). To control for the effect of competition on disclosure we include Fama-French 48 industry concentration ratio (HHI). We further include firm size ($SIZE$), because large firms tend to disclose more (Lang and Lundholm, 1993; Kasznik and Lev, 1995; Baginski and Hassell, 1997). We also control for whether the firm is

[5]This identification strategy requires firms to be aware of the IDD-related cases that set a precedent on their headquarters states. Li et al. (2018) argue that it is reasonable to consider this as valid assumption for two reasons. First, firms are expected to monitor trade secrets laws because the protection of trade secrets is key for maintaining firms' competitive advantages. Second, firms legal counsels are likely to be aware of IDD precedent-setting cases discussed in legal journals, and pervasive media coverage of prominent cases likely increases market awareness on IDD-related cases.

[6]See Hoberg and Phillips (2016) for details on TNIC score construction. Data on TNIC score is available at: http://hobergphillips.usc.edu/industryclass.htm

audited by a big 4 auditor ($BIG4$), the composition of the board of directors ($BOARD$), and the proportion of institutional ownership ($INST$) to capture the effects of corporate governance on voluntary disclosure (Hirst et al., 2008). We include the number of analyst following (AF) to account for the potential demand for voluntary disclosure analyst following (Ajinkya et al., 2005; Healy and Palepu, 2001; Hirst et al., 2008). To capture capital market incentives for voluntary disclosure we include controls for whether the firm announces M&A deals (MA) or seasoned equity offerings (SEO) during the year succeeding the year of disclosure. Finally, following Li et al. (2018), to control for economic conditions at the state level we include state real GDP growth rate (ΔGDP) and state unemployment rate (U_RATE). See Appendix B for variable definitions.

We include a set of fixed-effects in model (1). First, μ_i is the firm fixed-effect, which captures time-invariant unobservable committed firm characteristics that might be associated with firm voluntary disclosure. Second, η_s is the state fixed-effects, that allows us to account for time-invariant across state differences in disclosure, and change in headquarters location. Finally, we have year fixed-effects, θ_t, to control for time trends or economic shocks that might affect all firms in the sample (e.g. Reg FD). Standard errors are clustered at the state level to address potential autocorrelation concerns.

Coefficient β_1 in model (1) captures how peer firms in non-IDD adopting states respond to lower levels of disclosure due to IDD adoption. A negative (positive) β_1 would indicate an increase (decrease) in the disclosure of customer information. Klasa et al. (2018) identify 21 states that adopt IDD during the period 1919-2011.[7] To the extent that less disclosure from industry leaders might send a stronger signal to the capital-markets (e.g. reflect industry trends), we expect information-transfers and peer firm's response to be larger. To test whether firm's reaction is stronger when the closest peer is an industry leader headquartered in an IDD adopting state, we consider the interaction $PEER * LEADER$ in model (1). Where $LEADER$ is an indicator variable that takes value one if the closest peeri is an industry leader in year t. We consider a firm as an industry leader, in year t, if its market value is among the top decile of the industry in that year, where industry is defined using Fama-French 48 industry classification.

3.3.1 Type of Competition

We explore potential cross-sectional variation on peer's response to IDD adoption. Prior literature suggests that information-transfers might differ depending on the type of product-market competition (Kim et al., 2008; Desir, 2012). We follow Bloomfield (2018), and use several proxies in an attempt to capture different sources of product-market competition. Our first measure is based on Kedia (2006)

[7] See Appendix A for details on IDD adopting states dates.

who classifies firms as facing strategic complement (substitutes) interactions when the slope of the firm's reaction function is positive (negative). To obtain the sign of the firm's reaction function we estimate the following model for each industry-quarter:

$$\Delta \frac{\Delta \pi_{i,t}}{\Delta x_{i,t}} = \beta_1 x_{i,t} \Delta x_{i,t} + \beta_2 \Delta x_{i,t} + \beta_3 x_{j,t} \Delta x_{i,t} + \beta_4 \Delta x_{j,t} \tag{3.2}$$

Where:

$i = firm$,

$j = firm\ i's\ rivals$ (defined at the Fama-French 48 Industry level),

$\pi = quarterly\ profits$,

$x = quarterly\ revenues.$

The estimator of the sign of the strategic interaction is given by $\hat{\beta}_3 x_{j,t} + \hat{\beta}_4$. The intuition of this measure is as follows, the left-hand side captures the returns to strategic actions, then $\hat{\beta}_3 x_{j,t} + \hat{\beta}_4$ reflect how the returns to strategic actions change as a consequence of firm i's rivals strategic actions ($x_{j,t}$). We follow Bloomfield (2018), and aggregate $\hat{\beta}_3 x_{j,t} + \hat{\beta}_4$ over all firm-years in a an industry to obtain an industry-level measure of strategic interactions. If the industry median sign is positive (negative) we consider strategic actions as complements (substitutes).[8]

The second measure captures the importance of capacity constraints in competition (Maggi, 1996; Bloomfield, 2018). Firms in industries with more production flexibility (i.e. less capacity constraints) are more likely to engage in a Bertrand type of competition, while firms with less production flexibility (i.e. more capacity constraints) are more likely to engage in a Cournot type of competition. Following Bloomfield (2018) we calculate the average ratio of property plant and equipment to total assets by industry year, using the Fama-French 48 industry classification, and define industries as having high (low) production flexibility if the average ratio is below (above) the median.

The third measure captures firms efforts to differentiate their products from their competitors. Following Bloomfield (2018) we calculate the average R&D and advertising expenditures by industry year, using the Fama-French 48 industry classification, and define industries as having high (low) product differentiation if the average is below (above) the median.

[8]The underlying assumptions for this measure to be an unbiased measure of competition are (1) that demand is linear, and (2) marginal costs are flat. See Kedia (2006) for more details on this measure.

3.4 Sample and Results

Our sample includes all firm-year observations during the period 1994-2010. Following Li et al. (2017) we use Bill McDonald 10-K Headers Database to obtain information regarding the historical location of each firm headquarters.[9] We exclude all firms headquartered outside the U.S. and firms that might be subject to specific institutional and regulatory constraints (SIC 60-69). Finally, we exclude all firm-year observations of firms in IDD adopting sates, and after imposing all data requirements, our final sample includes 10,814 firm-year observations over the period 1994-2010.

Table 1 panel A presents the description of the sample selection process. Panel B of table 1 presents the sample distribution by state, the number of firm-year observations in our final sample is balanced among the number of observations of firms headquartered in IDD and non-IDD adopting sates. Table 1 panel C, suggests that there is enough variation in the IDD adoption at the state-level in our sample period. Figure 1 shows states adopting/rejecting IDD during our sample period. Appendix A presents variables definitions and panel D of table 1 reports the descriptive statistics on the variables used in estimating model (1).

3.4.1 Peers response to IDD adoption

Table 2 present the results for the estimation of model (1). The coefficient on $PEER$ in column (1), β_1, is negative and only statistically significant at the 10% level for a one tailed test. In terms of the economic magnitude, $\beta_1 = -0.009$, implies that firms in non-IDD states are 3.08% less likely to conceal customer information after the adoption of IDD in the state where its closest peer is headquartered. The coefficient on $PEER$ in column (3) is not statistically significant different from zero.

In columns (2) and (4), we consider the effects of IDD adoption when the closest peer is an industry leader. The coefficient on the interaction term, $PEER * LEADER$, is negative and statistically significant at the 1% level in column 2. Firms in non-IDD states whose closest peer is an industry leaders in an IDD adopting state, are are 11.29% less likely to conceal customer information relative to non-IDD firms whose closest peer is not an industry leader. If we consider $R2$ as the dependent variable (column 4), β_3 remains negative and statistically significant different from zero at the 5% level.

These results suggests that firms headquartered in non-IDD states whose closest peer is headquartered in an IDD adopting states, respond to IDD adoption disclosing more information on customer identity when when its closest peer is an industry leader. This is consistent with the argument that

[9]10-K Headers Database is available at https://www3.nd.edu/mcdonald/10-K_Headers/10-K_Headers.html

managers might take actions (i.e. voluntary disclosure) to mitigate the effects of negative information-transfers (Desir, 2012).

3.4.2 Product Market Competition

Our motivation in this section is to determine whether product market competition affects non-IDD peer firms response to IDD adoption. First, we partition our sample using Kedia (2006) measure of strategic interactions. Table 3 column (1), presents the results of estimating model (1) for firms in industries facing strategic substitute interactions from rival firms, while column (2) presents the results for firms facing strategic complement interactions. In both cases the coefficient on $PEER*LEADER$ is negative, but is only statistically significant for firms in industries facing strategic complement interactions.

Next, columns (3) and (4) of table 3 presents the results of estimating model (1) partitioning our sample among firms with high and low production flexibility. We find evidence of stronger peer response to IDD adoption for firms in industries with low product flexibility. The coefficient on $PEER$ in column (4) is is negative and statistically significant at the 5%. In terms of the economic significance, $\beta_1 = -0.015$, implies that firms in non-IDD states whose closest peer is headquartered in an IDD state are 6.5% less likely to conceal customers identity, the magnitude increases in 23.33% if the closest peer is an industry leader ($\beta_3 = -0.055$).

Finally, we examine the effect of product differentiation on peer firms response to IDD adoption. Results on columns (5) and (6) suggests that there is no statistically meaningful effect of product market differentiation on peers response to IDD adoption.

Overall, results presented in table 3 suggest that product market competition, proxied by strategic interactions and production flexibility plays an important role on peer firms response to IDD adoption.

3.5 Management Forecasts

Our purpose in this section is to analyze whether firms respond to negative information-transfers using other types of disclosure. Managers' decision to voluntary disclose information will involve a cost-benefit analysis Healy and Palepu (2001); Hirst et al. (2008), in this sense is likely that managers will choose the least costly venue to voluntary disclose their private information in response to negative information-transfers.

In this section we focus on management forecasts. Relative to the proxy used in our main analysis (i.e. disclosure of customer indentity), management forecasts can be considered as non-proprietary disclosure (Ellis et al., 2012). In particular we focus in annual forecasts of sales and earnings per share(EPS). We use I/B/E/S guidance database to identify those firms issuing good news sales and EPS management forecasts for the next fiscal year. We consider a forecast to be good news when its value is higher that the most recent analyst consensus forecast.

Table 4 present the results for the estimation of model (1) when the dependent variable is a good news management forecasts. The results for good news sales forecasts (column 1) indicate that firms respond to IDD adoption in the states where its closest peer is headquartered issuing more good news sales forecasts. In terms of the economic magnitude, $\beta_1 = 0.015$, implies that firms in non-IDD states are30.7% more likely to issue good news sales forecasts after the adoption of IDD in the state where its closest peer is headquartered. Results in column (2) suggest that leadership status of the closest peer do not play any role in firms response to IDD adoption. Finally, results in columns (3) and (4) indicate that firms do not issue more good news management forecasts in response to negative information transfers.

3.6 Summary and Conclusion

We study how firms respond to lower levels of disclosure from peers. Firms might respond to lower levels of disclosure from rivals to mitigate potential negative information-transfers. We exploit the staggered adoption of IDD as an exogenous shock to the information environment of peer firms in non-IDD states. Preliminary results indicate that peer firms in non-IDD states are less likely to conceal customer identity after IDD adoption. These results are stronger when industry leaders are headquartered in IDD adopting states. Our results are robust to excluding states that have no variation in IDD adoption during our sample period, and to excluding peers in non-neighbor states to control for potential local economic conditions confounding. We also find that the results are stronger for firms that face strategic substitute interactions from rivals and for firms in industries with higher product market differentiation.

We contribute to the literature on information-transfers and disclosure by showing how firms respond to lower levels of disclosure from rivals by increasing their own disclosure to counteract potential negative information-transfers. Additionally, we show how peer firms' response depend on product market competition.

Appendix A - IDD Adoption

Klasa et al. (2018) identify the main legal cases addressing IDD in each state, and based on the court rulings identify the precedent-setting cases adopting IDD as the first case in which, (a) court ruling recognizes the IDD can be used to prevent a former employee of the firm form working at a competing firm, and (b) court ruling on the use of the IDD is not justified by referring to a previous case in the same state that adopt the IDD. For the precedent-setting cases rejecting IDD identification, Klasa et al. (2018) focus on legal cases that revert prior courts' adoption of the IDD, where the case decision is the first one to reject the IDD in the state. Klasa et al. (2018) argue that state courts will consider preceding-setting cases as 'case law', and therefore follow its ruling in the future. Table A.1 details the 21 sates and dates of IDD adoption identified by Klasa et al. (2018). See table 1 in Klasa et al. (2018) for a list of IDD precedent-setting cases.

Table A.1: States Adopting/Rejecting the Inevitable Disclosure Doctrine

Abbreviation	State	Adoption Date	Rejection Date
AR	Arkansas	3/18/1997	-
CT	Connecticut	2/28/1996	-
DE	Delaware	5/5/1964	-
FL	Florida	7/11/1960	5/21/2001
GA	Georgia	6/29/1998	-
IA	Iowa	4/1/1996	-
IL	Illinois	2/9/1989	-
IN	Indiana	7/12/1995	-
KS	Kansas	2/2/2006	-
MA	Massachusetts	10/13/1994	-
MI	Michigan	2/17/1966	4/30/2002
MO	Missouri	11/2/2000	-
MN	Minnesota	10/10/1986	-
NC	North Carolina	6/17/1976	-
NJ	New Jersey	4/27/1987	-
NY	New York	12/5/1919	-
OH	Ohio	9/29/2000	-
PA	Pennsylvania	1/19/1982	-
TX	Texas	5/28/1993	4/3/2003
UT	Utah	1/30/1998	-
WA	Washington	12/301997	-

Appendix B - Variable Definitions

Name	Definition
$RATIO\_1$	Is the percentage of unidentified customers in year t. From COMPUSTAT segment reporting, we consider customer as unidentified if item cnms is equal to "not reported", "other", or "customer".
$RATIO\_2$	Is the sales-weighted percentage of unidentified customers.
$PEER$	Is an indicator variable that takes value one for firms with headquarters in non-IDD adopting states, when its closest peer is headquartered in IDD adopting states, in a given year t. We identify the closest peer firm based in the TNIC score developed by Hoberg and Phillips (2016).
$MISS\_RD$	Indicator variable equal to one if R&D expenses (COMPUSTAT item xrd) is missing.
RD_EXP	Total R&D expenses (COMPUSTAT item xrd) divided by total sales (COMPUSTAT item sale).
$INTAN$	Total intangible assets (COMPUSTAT item intan) divided by total assets (COMPUSTAT item at).
AD_EXP	Total advertising expenses (COMPUSTAT item xad) divided by total sales (COMPUSTAT item sale).
HHI	Is measured using the Herfindal-Hirschman Index, which is equal to the sum of the squares of the market shares of the firms within an industry. Industry is defined according to the Fama-French 48 industry classification.
$SIZE$	Natural logarithm of total assets in year t. (COMPUSTAT item at).
$BIG4$	Indicator variable taking value one if the auditor in year t is a big-4 firms. (COMPUSTAT item au).
$BOARD$	Is defined as the proportion of independent directors within the board. We get board of directors data from BoardEx.
$INST$	Shares held by institutional investors as a percentage of total outstanding shares (Thomson Reuters 13F item instown_perc) in year t.
AF	Is natural log of one plus the number of analyst (IBES Summary item numest) following the company in year t. For companies not covered by IBES AF is set equal to zero.
MA	Indicator variable taking value one if the firm announce an M&A deal during year t. We get M&A deals data from SDC.
SEO	Indicator variable taking value one if the firm announce a seasoned equity offering during year t. We get SEO data from SDC.
ΔGDP	Sate annual real GDP growth rate from the Bureau of Economic Analysis.
U_RATE	Sate annual unemployment rate from teh Bureau of Labor Statistics.

Figure 1: States Adopting/Rejecting the Inevitable Disclosure Doctrine

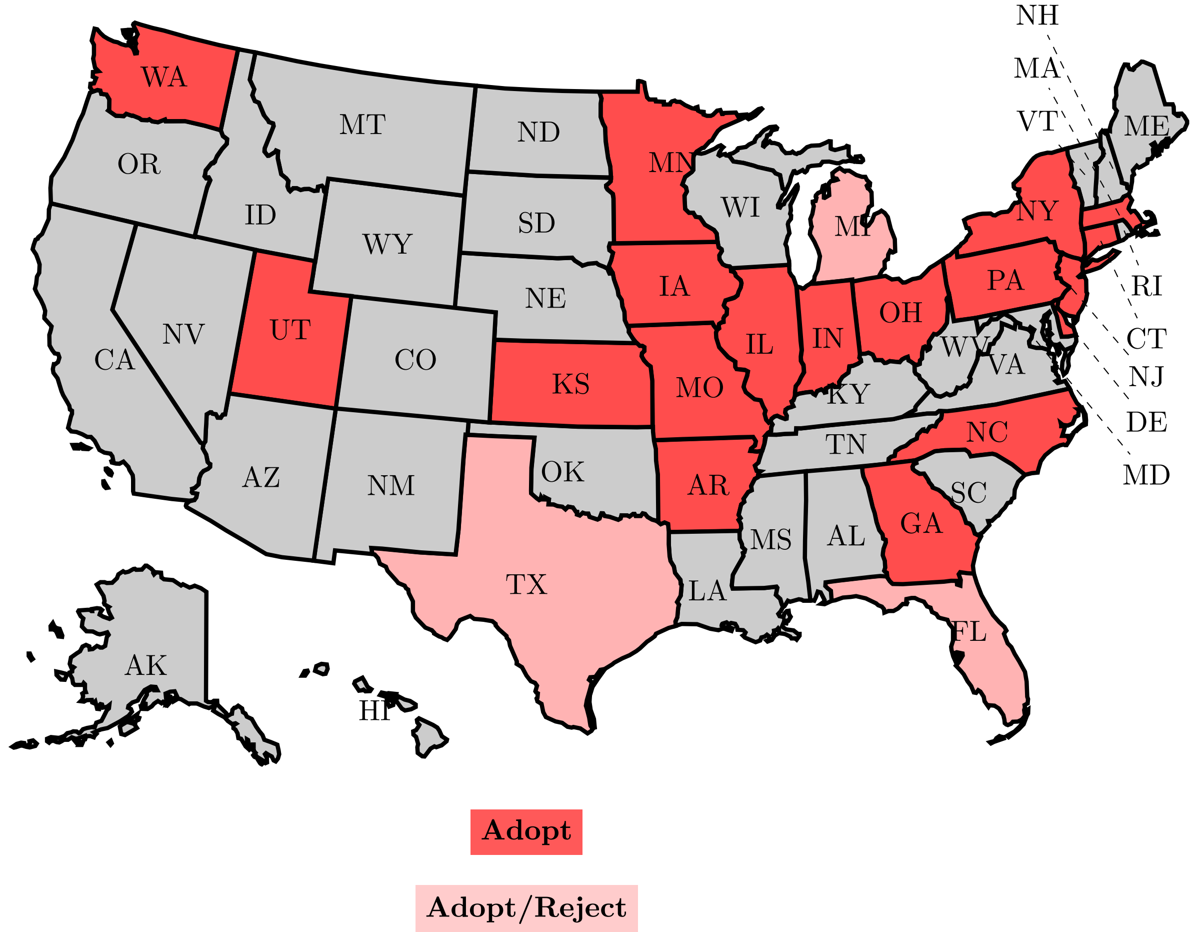

Table 1

Panel A: Sample Selection

Sample: Customers Identity Disclosure	Observations
McDonald's headquarters data (1994 to 2010)	161,561
- Observations without customer, financial & controls data	(123,604)
- Financial Firms	(2,171)
- Firms without at least one customer representing 10% or more of their sales	(7,441)
- Firms in IDD adopting states	(17,531)
Final Sample	10,814

Table 1

Panel B: Firm-Year Observations by State

State	IDD=0	IDD=1	Total
AK	16	0	16
AL	131	0	131
AR	23	103	126
AZ	468	0	468
CA	7,144	0	7,144
CO	1,207	0	1,207
CT	69	661	730
DC	15	0	15
DE	0	71	71
FL	838	687	1,525
GA	216	613	829
HI	49	0	49
IA	12	88	100
ID	103	0	103
IL	0	1,057	1,057
IN	27	301	328
KS	109	40	149
KY	148	0	148
LA	235	0	235
MA	27	2,057	2,084
MD	564	0	564
ME	19	0	19
MI	326	458	784
MN	0	1,108	1,108
MO	126	289	415
MS	88	0	88
MT	60	0	60
NC	0	654	654
ND	13	0	13
NE	107	0	107
NH	155	0	155
NJ	0	1,894	1,894
NM	57	0	57
NV	210	0	210
NY	0	2,826	2,826
OH	390	557	947
OK	398	0	398
OR	401	0	401
PA	0	1,337	1,337
RI	123	0	123
SC	135	0	135
SD	22	0	22
TN	359	0	359
TX	1,548	1,938	3,486
UT	90	319	409
VA	638	0	638
VT	40	0	40
WA	76	473	549
WI	449	0	449
WV	35	0	35
WY	11	0	11
Total	**17,277**	**17,531**	**34,808**

Table 1

Panel C: Firm-Year Observations in IDD Adopting States by Year

State/Year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
AR	0	0	1	9	9	4	7	8	6	5	6	8	8	9	9	8	6	103
CT	0	4	48	60	62	38	49	50	51	44	43	42	41	41	31	31	26	661
DE	5	7	7	6	6	4	5	5	2	6	5	2	2	2	2	3	2	71
FL	77	78	101	119	115	83	114	0	0	0	0	0	0	0	0	0	0	687
GA	0	0	0	0	58	39	61	53	56	54	49	50	45	41	37	39	31	613
IA	0	1	8	9	7	6	4	5	7	5	5	5	5	4	6	4	7	88
IL	53	59	70	73	83	51	64	61	65	62	56	67	66	57	59	55	56	1,057
IN	0	21	21	22	24	16	21	18	19	19	19	17	17	15	16	18	18	301
KS	0	0	0	0	0	0	0	0	0	0	0	1	8	7	8	7	9	40
MA	75	115	145	175	158	106	153	138	136	112	106	107	105	113	109	105	99	2,057
MI	46	54	56	69	65	48	62	58	0	0	0	0	0	0	0	0	0	458
MN	60	67	87	81	83	64	79	74	75	69	65	59	63	57	42	43	40	1,108
MO	0	0	0	0	0	0	18	28	29	26	26	29	27	25	25	28	28	289
NC	34	33	39	47	49	38	39	41	41	39	39	38	36	34	38	37	32	654
NJ	94	90	124	143	140	102	134	130	119	111	106	107	112	108	97	94	83	1,894
NY	146	155	198	229	216	171	199	189	175	147	136	145	140	148	145	152	135	2,826
OH	0	0	0	0	0	0	56	57	59	49	46	51	52	49	44	49	45	557
PA	74	63	88	100	89	60	86	92	95	78	84	78	80	76	69	63	62	1,337
TX	186	194	226	257	223	181	227	233	211	0	0	0	0	0	0	0	0	1,938
UT	0	0	0	2	30	29	28	24	28	25	24	21	26	22	19	21	20	319
WA	0	0	0	31	36	30	38	42	42	35	34	35	33	32	28	31	26	473
# of States	11	14	15	17	18	18	20	19	18	17	17	18	18	18	18	18	18	21
# of Firms	850	941	1,219	1,432	1,453	1,070	1,444	1,306	1,216	886	849	862	866	840	784	788	725	17,531

Table 1

Panel D: Descriptive Statistics

	Mean	Std. Dev.	1%	Q1	Median	Q3	99%
$RATIO\_1$	0.413	0.429	0.000	0.000	0.321	1.000	1.000
$RATIO\_2$	0.419	0.452	0.000	0.000	0.183	1.000	1.000
$PEER$	0.167	0.373	0.000	0.000	0.000	0.000	1.000
$MISS\_RD$	0.367	0.482	0.000	0.000	0.000	1.000	1.000
RD_EXP	0.195	0.605	0.000	0.000	0.016	0.155	3.319
$INTAN$	0.096	0.146	0.000	0.000	0.019	0.141	0.595
AD_EXP	0.007	0.021	0.000	0.000	0.000	0.001	0.112
HHI	0.062	0.042	0.026	0.033	0.048	0.070	0.201
$SIZE$	4.630	2.001	-0.057	3.220	4.645	6.056	8.897
$BIG4$	0.622	0.485	0.000	0.000	1.000	1.000	1.000
MA_{t+1}	0.069	0.253	0.000	0.000	0.000	0.000	1.000
SEO_{t+1}	0.036	0.187	0.000	0.000	0.000	0.000	1.000
ΔGDP	1.768	2.803	-5.400	0.300	2.400	3.600	7.200
U_RATE	6.025	2.182	2.700	4.700	5.700	6.800	12.100
$BOARD$	0.380	0.453	0.000	0.000	0.000	1.000	1.000
$INST$	0.309	0.311	0.000	0.003	0.212	0.563	0.979
AF	1.058	1.039	0.000	0.000	1.099	1.946	3.178

Table 2

IDD and Disclosure of Customer Information of Peers in Non-IDD States

	(1) R1	(2) R1	(3) R2	(4) R2
$PEER$	-0.009†	-0.007	0.003	0.005
	(0.006)	(0.006)	(0.007)	(0.007)
$LEADER$	-	0.005	-	0.002
	-	(0.014)	-	(0.011)
$PEER * LEADER$	-	-0.033***	-	-0.028**
	-	(0.012)	-	(0.012)
$MISS\_RD_{t-1}$	0.029*	0.028*	0.033*	0.033*
	(0.016)	(0.016)	(0.017)	(0.017)
RD_EXP_{t-1}	0.010	0.010	0.013	0.013
	(0.010)	(0.010)	(0.009)	(0.009)
$INTAN_{t-1}$	0.026	0.026	0.023	0.024
	(0.023)	(0.023)	(0.047)	(0.047)
AD_EXP_{t-1}	0.220	0.224	0.103	0.107
	(0.144)	(0.145)	(0.123)	(0.123)
HHI_{t-1}	0.107	0.107	0.039	0.039
	(0.281)	(0.281)	(0.302)	(0.302)
$SIZE_{t-1}$	-0.018***	-0.018***	-0.020***	-0.020***
	(0.005)	(0.005)	(0.006)	(0.006)
$BIG4_{t-1}$	-0.010	-0.010	-0.004	-0.004
	(0.009)	(0.009)	(0.013)	(0.013)
$BOARD_{t-1}$	-0.011	-0.011	-0.009	-0.009
	(0.009)	(0.009)	(0.012)	(0.012)
$INST_{t-1}$	0.006	0.005	0.004	0.004
	(0.018)	(0.018)	(0.017)	(0.017)
AF_{t-1}	0.020***	0.020***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
MA_{t+1}	-0.009	-0.009	-0.000	-0.000
	(0.013)	(0.013)	(0.011)	(0.011)
SEO_{t+1}	0.020**	0.021**	0.012	0.012
	(0.010)	(0.010)	(0.011)	(0.011)
ΔGDP_t	-0.002	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
U_RATE_t	0.002	0.002	0.001	0.001
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	10,814	10,814	10,814	10,814
Number of Firms	2,675	2,675	2,675	2,675
State F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	State	State	State	State
Adj_R^2	0.748	0.748	0.740	0.739

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$, † $p<0.1$ (for one tail test)

Table 3

Disclosure of Customer Information of Peers in Non-IDD States and Product Market Competition

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	Strategic		Prod. Flex.		Prod. Diff.	
Variable: R1	Subs.	Comp.	High	Low	High	Low
$PEER$	-0.012	-0.004	0.001	-0.015**	-0.012	0.011
	(0.013)	(0.006)	(0.009)	(0.006)	(0.008)	(0.018)
$LEADER$	0.013	0.001	0.003	-0.006	-0.012	0.077***
	(0.011)	(0.017)	(0.016)	(0.019)	(0.009)	(0.027)
$PEER * LEADER$	-0.001	-0.049**	0.003	-0.055**	-0.024	-0.066
	(0.039)	(0.022)	(0.019)	(0.023)	(0.018)	(0.043)
$MISS\_RD_{t-1}$	0.041	0.020	-0.007	0.046*	0.040**	-0.026
	(0.031)	(0.016)	(0.022)	(0.024)	(0.015)	(0.031)
RD_EXP_{t-1}	-0.022	0.014	-0.002	0.011	0.012	-0.004
	(0.035)	(0.008)	(0.005)	(0.011)	(0.010)	(0.003)
$INTAN_{t-1}$	0.073	0.006	0.090*	-0.027	0.021	0.017
	(0.056)	(0.023)	(0.052)	(0.042)	(0.034)	(0.070)
AD_EXP_{t-1}	0.685**	0.137	-0.113	0.475**	0.219	0.276
	(0.320)	(0.136)	(0.314)	(0.232)	(0.187)	(0.340)
HHI_{t-1}	0.217	-0.290	0.130	0.307	0.939***	-0.875
	(0.325)	(0.411)	(0.437)	(0.301)	(0.326)	(0.524)
$SIZE_{t-1}$	-0.041***	-0.008	-0.030***	0.007	-0.015***	-0.017
	(0.014)	(0.005)	(0.007)	(0.006)	(0.005)	(0.018)
$BIG4_{t-1}$	0.013	-0.022***	-0.011	-0.018	-0.015	-0.008
	(0.019)	(0.007)	(0.012)	(0.011)	(0.011)	(0.021)
$BOARD_{t-1}$	0.025	-0.029***	-0.009	-0.014	-0.012	-0.025
	(0.022)	(0.010)	(0.012)	(0.023)	(0.010)	(0.024)
$INST_{t-1}$	0.006	0.007	0.023	-0.013	0.003	-0.038
	(0.027)	(0.024)	(0.023)	(0.022)	(0.019)	(0.047)
AF_{t-1}	0.023*	0.018**	0.027***	-0.002	0.016***	0.039**
	(0.012)	(0.007)	(0.010)	(0.011)	(0.006)	(0.017)
MA_{t+1}	-0.013	-0.005	-0.008	-0.013	-0.010	-0.002
	(0.013)	(0.013)	(0.019)	(0.009)	(0.016)	(0.014)
SEO_{t+1}	0.055*	0.010	0.019	0.024	0.019	0.020
	(0.032)	(0.012)	(0.012)	(0.019)	(0.011)	(0.027)
ΔGDP_t	-0.000	-0.002	-0.003	-0.002	-0.003	-0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
U_RATE_t	0.006	-0.001	0.007	-0.011*	0.002	-0.008
	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.009)
Observations	3,517	7,297	6,620	4,194	8,007	2,807
Number of Firms	836	1,840	1,636	1,263	2,067	899
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	State	State	State	State	State	State
Adj_R^2	0.768	0.781	0.700	0.651	0.651	0.760

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4

Good News Management Forecasts of Peers in Non-IDD States

	(1) Sales Forecasts	(2) Sales Forecasts	(3) EPS Forecast	(4) EPS Forecast
$PEER$	0.015***	0.014**	-0.004	-0.007
	(0.005)	(0.006)	(0.006)	(0.005)
$LEADER$	-	0.008	-	-0.002
	-	(0.018)	-	(0.007)
$PEER * LEADER$	-	-0.000	-	0.037
	-	(0.034)	-	(0.041)
$MISS\_RD_{t-1}$	-0.019	-0.019	0.004	0.004
	(0.012)	(0.012)	(0.013)	(0.013)
RD_EXP_{t-1}	-0.007	-0.007	-0.010***	-0.010***
	(0.009)	(0.009)	(0.002)	(0.002)
$INTAN_{t-1}$	0.101***	0.101***	0.062***	0.061***
	(0.020)	(0.020)	(0.013)	(0.013)
AD_EXP_{t-1}	-0.153	-0.156	-0.197***	-0.202***
	(0.142)	(0.143)	(0.069)	(0.070)
HHI_{t-1}	-0.189	-0.187	0.206	0.206
	(0.193)	(0.193)	(0.235)	(0.235)
$SIZE_{t-1}$	0.009**	0.009**	0.002	0.002
	(0.004)	(0.004)	(0.003)	(0.003)
$BIG4_{t-1}$	0.014**	0.014**	0.005	0.005
	(0.006)	(0.006)	(0.007)	(0.007)
$BOARD_{t-1}$	0.037***	0.037***	0.021	0.021
	(0.008)	(0.008)	(0.013)	(0.013)
$INST_{t-1}$	0.028	0.027	0.023	0.023
	(0.026)	(0.027)	(0.016)	(0.016)
AF_{t-1}	0.014	0.014	0.006	0.006
	(0.010)	(0.010)	(0.006)	(0.006)
MA_{t+1}	-0.005	-0.005	0.011	0.011
	(0.007)	(0.007)	(0.011)	(0.011)
SEO_{t+1}	-0.029**	-0.029**	-0.019**	-0.020**
	(0.011)	(0.011)	(0.008)	(0.008)
ΔGDP_t	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
U_RATE_t	-0.004	-0.004	-0.007**	-0.007**
	(0.004)	(0.004)	(0.003)	(0.003)
Observations	10,814	10,814	10,814	10,814
Number of Firms	2,675	2,675	2,675	2,675
State F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	State	State	State	State
Adj_R^2	0.121	0.121	0.0673	0.0677

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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